ESSAYS ON EMPIRICAL TIME SERIES MODELING

WITH CAUSALITY AND STRUCTURAL CHANGE

A Dissertation

by

JIN WOONG KIM

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2006

Major Subject: Agricultural Economics

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Approved by:

Co-Chairs of Committee,	David J. Leatham
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ABSTRACT

Essays on Empirical Time Series Modeling with Causality and Structural Change.

(August 2006)

Jin Woong Kim, B.S., Hankuk University of Foreign Studies;

M.S., Sogang University

Co-Chairs of Advisory Committee: Dr. David J. Leatham
Dr. David A. Bessler

In this dissertation, three related issues of building empirical time series models for financial markets are investigated with respect to contemporaneous causality, dynamics, and structural change. In the first essay, nation-wide industry information transmission among stock returns of ten sectors in the U.S. economy is examined through the Directed Acyclical Graph (DAG) for contemporaneous causality and Bernanke decomposition for dynamics. The evidence shows that the information technology sector is the most root cause sector. Test results show that DAG from *ex ante* forecast innovations is consistent with the DAG from *ex post* fit innovations. This supports innovation accounting based on DAGs using *ex post* innovations.

In the second essay, the contemporaneous/dynamic behaviors of real estate and stock returns are investigated. Selected macroeconomic variables are included in the model to explain recent movements of both returns. During 1971-2004, there was a single structural break in October 1980. A distinct difference in contemporaneous causal structure before and after the break is found. DAG results show that REITs take the role

of a causal parent after the break. Innovation accounting shows significantly positive responses of real estate returns due to an initial shock in default risk but insignificant responses of stock returns. Also, a shock in short run interest rates affects real estate returns negatively with significance but does not affect stock returns.

In the third essay, a structural change in the volatility of five Asian and U.S. stock markets is examined during the post-liberalization period (1990-2005) in the Asian financial markets, using the Sup LM test. Four Asian financial markets (Hong Kong, Japan, Korea, and Singapore) experienced structural changes. However, test results do not support the existence of structural change in volatility for Thailand and U.S. Also, results show that the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) persistent coefficient increases, but the Autoregressive Conditional heteroskedasticity (ARCH) impact coefficient, implying short run adjustment, decreases in Asian markets.

In conclusion, when the econometric model is set up, it is necessary to consider contemporaneous causality and possible structural breaks (changes). The dissertation emphasizes causal inference and structural consistency in econometric modeling. It highlights their importance in discovering contemporaneous/dynamic causal relationships among variables. These characteristics will likely be helpful in generating accurate forecasts.

To my beloved brother

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CHAPTER I

INTRODUCTION

In financial modeling, it is necessary to have in-depth understanding about observed economic phenomena before formulating a specific model. Even if the econometric model used is the most popular among all alternatives, it may not provide a good explanation or forecast for economic variables without incorporating the intrinsic economic phenomena. Many financial econometric models overlook contemporaneous causality among variables, as well as the possibility of structural change.

The overall objective of this dissertation is to provide information on build dynamic market processes that address contemporaneous causality and structural change. Financial markets are not fully understood, especially with respect to dynamic causal flows among various sectors of the economy, structural breaks, and associated problems with appropriate data. Individual objectives for each chapter are following.

In chapter II, the objective is to find nation-wide industry information transmission among ten sectors in the U.S. economy. No studies in the last decade have undertaken an in-depth analysis of the transmission mechanism of stock returns across all industries within a national economy. This study will address this issue. Also, the stability in modeling structure will be studied through the comparison of variance-covariance

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This dissertation follows the format and style of the *Journal of Econometrics*.

structures within-sample-fit and out-of-sample forecasting innovations. This will allow us to investigate whether a standard Directed Acyclic Graphs (DAG) application in time series analysis is appropriate or not, with respect to modeling new information.

My objective in chapter III is to provide better explanations about recent differences in the dynamics of returns on REITs and equities in response to decreasing interest rate. This topic has not been addressed in previous studies. Also, a structural break test in REITs model will be included to investigate existence of possible structural break in REITs, which was just assumed or was searched by non-comprehensive tests in previous studies (Okunev *et al.* (2000), Ewing and Payne (2005), Payne (2003), and Chui *et al.* (2003)). The Sup LM test (Andrews, 1993) will be applied to investigate possible existence of (multiple) structural break(s) with unknown point(s). If the test result supports the existence of structural change(s), detection of change point(s) and the comparison of underlying dynamics will be studied to better understand implied differences.

The objective of chapter IV is to test for evidence of structural change in the volatility during post-liberalization in Asian financial markets using Sup LM test rather than previous other test methods. The current literature has not comprehensively covered structural change in volatility behavior in Asian financial markets. It is important for investors, analysts, and policy makers to measure accurate volatility because it implies useful information for prediction of market risk of price change. Possibility for existence of multiple structural changes will be discussed. Moreover, if there exist structural change(s) in volatility, characteristics of the structural change(s) is(are) studied using estimation result of conditional heteroskedastic model.

CHAPTER II

THE CAUSAL MODELING ON EQUITY MARKET INNOVATIONS: FIT OR FORECASTS?

2.1 Introduction

Innovation accounting from multiple time series is useful in the analysis of contagion paths of unexpected impacts of a specific variable. Since Bernanke (1986) and Sims (1986), a number of papers have suggested that the Choleski decomposition may provide misleading impulse-responses and forecast variance decompositions from a Vector Autoregression (VAR) or Error Correction Model (ECM). The Choleski decomposition applies a just-identified contemporaneous structure, which is not necessarily supported by prior economic knowledge or by the causal structure embedded in the empirical data. Bernanke (1986) relaxes the restriction of a just-identified structure for the innovations and imposes an over-identified casual order among variables. In its most commonly used form, this over-identified structure comes from the researcher in the form of subjective or theoretical-based knowledge.

Recently, Swanson and Granger (1997) have suggested that researchers consider modeling observed innovations from a VAR as a Directed Acyclical Graph (DAG), where empirical evidence on vanishing correlation or partial correlation is used to indicate the over-identifying structure on innovations. Bessler and Lee (2000) follow

Swanson and Granger and apply PC algorithm (Spirtes, Glymour, and Scheines 2000) to identify such a DAG (structure) on observed innovations based on within sample fit. They find empirical evidence from historical U.S. data that money supply was not exogenous in the late 1800's. Money was determined in contemporaneous time by movements in the general price level and income. Bessler and Yang (2003) study DAGs constructed with innovations from error correction models fit to daily observations on indexes from nine world equity markets (S&P 500, FTSE, DAX, etc.). Again, within sample fit innovations are used as data for the construction of these DAGs.

Here, I investigate whether the use of innovations based on "within-sample fit" results in the same structural ordering (DAG) as innovations based on "out-of-sample forecasts." Motivation for such a study is that it is generally recognized that "fit" is not the same as "forecast" (Granger (1980)). As innovations in a series represent "new" information not contained in its historical past, a preferred method for generation of innovations would be to use the difference between the actual series and its forecast, and not the difference between the actual series and its fit value (within-sample-forecast). The usual practice, of course, is to use innovations based on fit because they are easier to obtain.

This chapter addresses questions of information transfer among aggregations of U.S. equity prices. While there is a literature in this area, it has not been a heavily researched field. Alli, Thapa and Yung (1994) show that information is transmitted across markets. Persons (1995) offers an evidence of inter-industry information transmission using stock market data, from 1965 to 1990. Strike announcements in the automobile industry negatively effect steel suppliers' equities. However, as Alli, Thapa, and Yung (1994) state, there has not appeared an in-depth analysis on the transmission mechanism of stock returns across all industries within a national economy. To my knowledge, this omission in the literature has not been effectively covered in the last decade.

Because there are a number of industries in the industrial peers – GICS, SICS, and NAICS – this paper utilizes sector level data which are classified as related industries in the GICS structure (Table 2.1).

This study examines the price transmission among 10 sector classifications of the U.S. stock market. The major offering is a comparison between causal relationships on innovations from *ex ante* and *ex post* forecasts. This comparison enables us to comment on the usual approach to innovation accounting, where within-sample-fit innovations are used to generate impulse response functions and forecast error variance decompositions. Further, and more substantively, the results offer evidence on recent information flows among equities from ten aggregates of the U.S. economy.

2.2 Data

The S&P 500 Global Industry Classification Standard (GICS) Index is used. It contains stock price indices for 10 sectors.[1] The GICS is an enhanced industry

[1] These sectors are: Consumer Discretionary (CD), Consumer Staple (CS), Energy (EN), Financials (FN), Health Care (HC), Industrials (ID), Information Technology (IT), Materials (MA), Telecommunication Services (TS), and Utilities (UT). See Standard & Poor's (2003a, 2003b). See Bhojraj et al., 2003 for an empirical study of this system.

Table 2.1
Description of S&P 500 GICS index

Sector	Industry Group	Industry	Sun-Industry
Consumer Discretionary (CD)	Automobiles & Components / Consumer Durables & Apparel / Hotels/ Restaurants & Leisure / Media, Retailing	Auto Components/ Automobiles/ Household Durables/ Leisure Equipment & Products/ Textiles/ Apparel & Luxury Goods/Hotels/ Restaurants & Leisure/ Media/ Distributors/ Internet & Catalog Retail/ Multiline Retail/Specialty Retail	Auto Parts & Equipment/ Tires & Rubber/ Automobile Manufacturers/ Motorcycle Manufacturers/ Consumer Electronics/ Home Furnishings/ Homebuilding/ Household Appliances/ Housewares & Specialties/ Leisure Products/ Photographic Products/ Apparel, Accessories & Luxury Goods/ Footwear/ Textiles/ Casinos & Gaming/ Hotels, Resorts & Cruise Lines/ Leisure Facilities/ Restaurants/ Advertising/ Broadcasting & Cable TV/ Movies & Entertainment/ Publishing/ Distributors/ Catalog Retail/ Internet Retail/ Department Stores/ General Merchandise Stores/ Apparel Retail/ Computer & Electronics Retail/ Home Improvement Retail/ Specialty Stores
Consumer Staples (CS)	Food & Staples Retailing / Food, Beverage & Tobacco / Household & Personal Products	Food & Staples Retailing/ Beverages/ Food Products/ Tobacco/ Household Products/ Personal Products	Drug Retail/ Food Distributors/ Food Retail/ Hypermarkets & Super Centers/ Brewers/ Distillers & Vintners/ Soft Drinks/ Agricultural Products/ Meat, Poultry & Fish (*)/ Packaged Foods & Meats/ Tobacco/ Household Products/ Personal Products
Energy (EN)	Energy	Energy Equipment & Services/ Oil & Gas	Oil & Gas Drilling/ Oil & Gas Equipment & Services/ Integrated Oil & Gas/ Oil & Gas Exploration & Production/ Oil & Gas Refining & Marketing & Transportation
Financials (FN)	Banks / Diversified Financials / Insurance/ Real Estate	Commercial Banks/ Thrifts & Mortgage Finance/ Diversified Financial Services/ Consumer Finance/ Capital Markets/ Insurance/ Real Estate	Diversified Banks/ Regional Banks/ Thrifts & Mortgage Finance/ Consumer Finance(*)/ Other Diversified Financial Services/ Multi-Sector Holdings/ Specialized Finance/ Consumer Finance/ Asset Management & Custody Banks/ Investment Banking & Brokerage/ Diversified Capital Markets/ Insurance Brokers/ Life & Health Insurance/ Multi-line Insurance/ Property & Casualty Insurance/ Reinsurance/ Real Estate Investment Trusts/ Real Estate Management & Development
Health Care (HC)	Health Care Equipment & Services / Pharmaceuticals & Biotechnology	Health Care Equipment & Supplies/ Health Care Providers & Services/ Biotechnology	Health Care Equipment/ Health Care Supplies/ Health Care Distributors/ Health Care Services/ Health Care Facilities/ Managed Health Care/ Biotechnology/ Pharmaceuticals

Table 2.1. (*Continued*)

Sector	Industry Group	Industry	Sun-Industry
Industrials (ID)	Capital Goods/ Commercial Servics & Supplies/ Transportation	Aerospace & Defense/ Building Products/ Construction & Engineering/ Electrical Equipment/ Industrial Conglomerates/ Machinery/ Trading Companies & Distributors/ Commercial Services & Supplies/ Air Freight & Logistics/ Airlines/ Marine/ Road & Rail/ Transportation Infrastructure	Aerospace & Defense/ Building Products/ Construction & Engineering/ Electrical Components & Equipment/ Heavy Electrical Equipment/ Industrial Conglomerates/ Construction & Farm Machinery & Heavy Trucks/ Industrial Machinery/ Trading Companies & Distributors/ Commercial Printing/ Data Processing Services(*)/Diversified Commercial Services/ Employment Services/ Environmental Services/ Office Services & Supplies/ Air Freight & Logistics/ Airlines/ Marine/ Railroads/ Trucking/ Airport Services/ Highways & Railtracks/ Marine Ports & Services
Information Technology (IT)	Software &Services/ Technology Hardware Equipment/Semiconductors & Semiconductor Equipment	Internet Software & Services/ IT Services/ Software/ Communications Equipment/ Computers & Peripherals/ Electronic Equipment & Instruments/ Office Electronics/ Semiconductors & Semiconductor Equipment	Internet Software & Services/ IT Consulting & Other Services/ Data Processing & Outsourced Services/ Application Software/ Systems Software/ Home Entertainment Software/ Communications Equipment/ Networking Equipment/ Telecommunications Equipment/ Computer Hardware/ Computer Storage & Peripherals/ Electronic Equipment Manufacturers/ Electronic Manufacturing Services/ Technology Distributors/ Office Electronics/ Semiconductor Equipment / Semiconductors
Materials (MA)	Materials	Chemicals/ Construction Materials/ Containers & Packaging/ Metals & Mining/ Paper & Forest Products	Commodity Chemicals/ Diversified Chemicals/ Fertilizers & Agricultural Chemicals/ Industrial Gases/ Specialty Chemicals/ Construction Materials/ Metal & Glass Containers/ Paper Packaging/ Aluminum/ Diversified Metals & Mining/ Gold/ Precious Metals & Minerals/ Steel/ Forest Products/ Paper Products/
Telecommunication Services (TS)	Telecommunication Services	Diversified Telecommunication Services/ Wireless Telecommunication Services	Alternative Carriers/ Integrated Telecommunication Services/ Wireless Telecommunication Services
Utilities (UT)	Utilities	Electric Utilities/ Gas Utilities/ Multi-Utilities & Unregulated Power/ Water Utilities	Electric Utilities/ Gas Utilities/ Multi-Utilities & Unregulated Power/ Water Utilities

Source: Standard and Poor’s (2003b, 2003c).
(*) : Disconnected after Apr. 30, 2003.

classification system developed by Standard & Poor (S&P) and Morgan Stanley Capital International (MSCI). The GICS system currently has four levels of detail: 10 sectors, 24 industry groupings, 62 industries, and 132 sub-industries. The initial value of each sector was set at 100 on Jan 2. 1995, and the values fluctuate over time according to the market valuation of the individual equities. The GICS index is divided by sectors, industry groups, industries, and sub-industries (Table 2.1). For the current study, data are daily over the time period Jan. 2, 1995 to Jul. 15, 2003. As shown in Fig. 2., the Information Technology (IT) Sector shows the strongest growth during the two years from late 1998, but falls at 2000. The Telecommunication Service sector also shows a similar trend as IT, even if its scale of movement (variation) is less than that of IT. The Health Care and Financials sectors show more muted growth, as their trends are positive with somewhat flatter shapes compared with other sectors. More rigorous analysis of these data follows.

2.3 Modeling

A Vector Error Correction Model (Vector ECM) is used to represent the dynamic properties of data. The Vector ECM representation is given as:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + e_t , \tag{2.1}$$

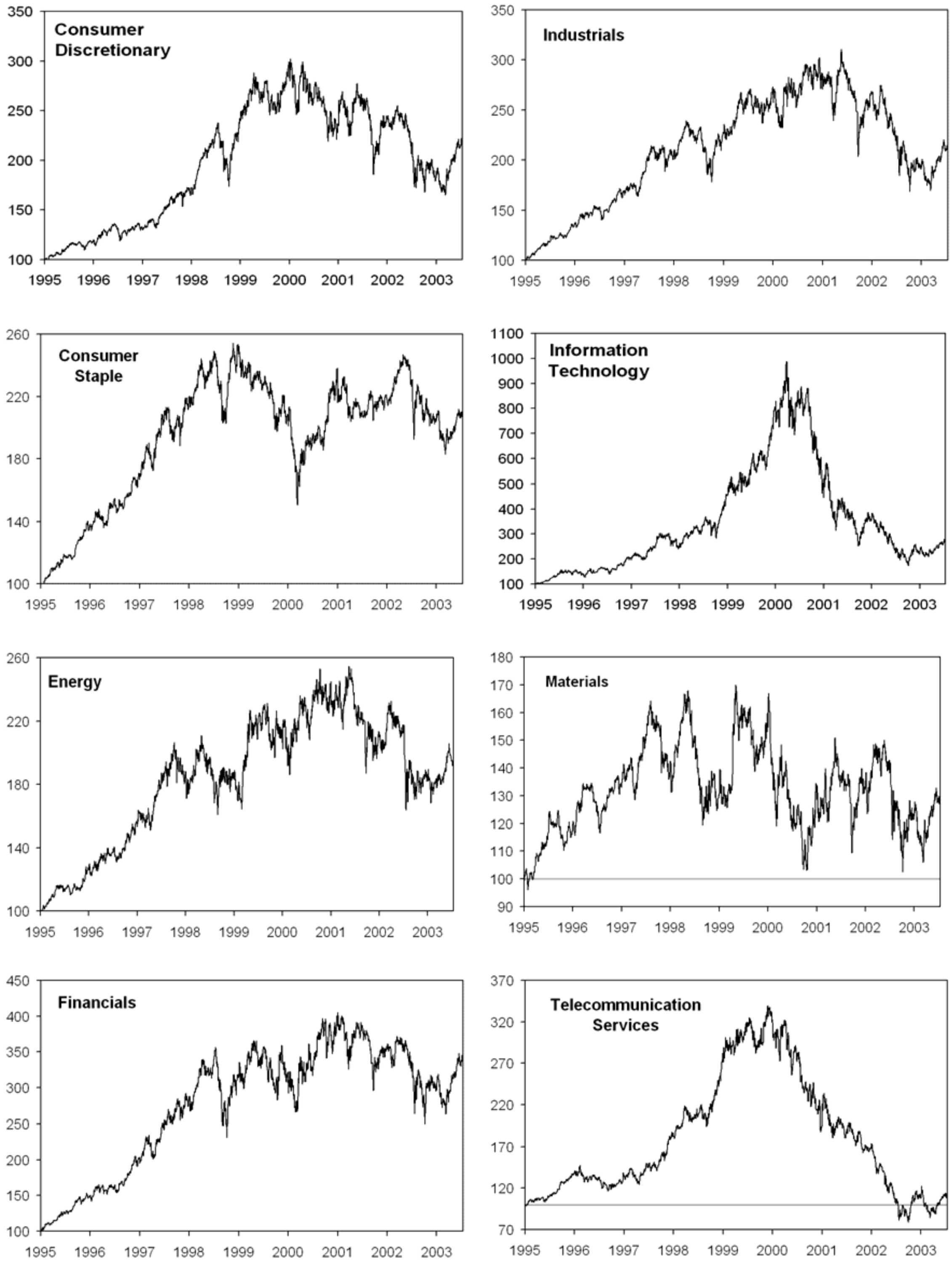

Fig. 2.1. Plots of sectors of the S&P 500 GICS indices.

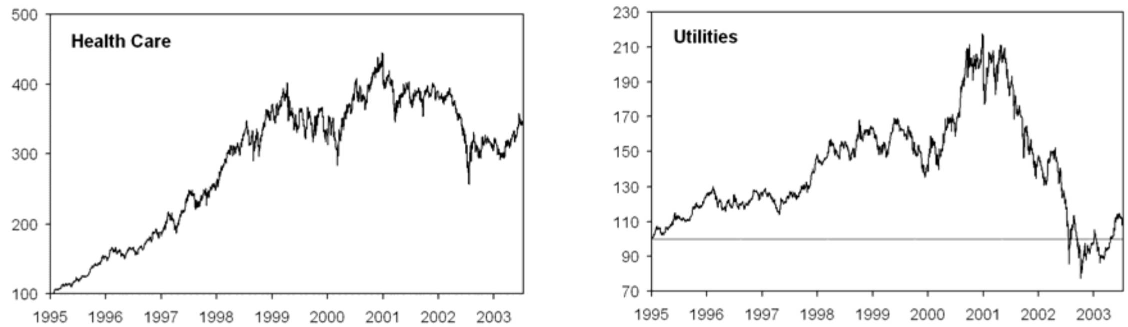

Fig. 2.1. (*Countinued*)

where, $e_t \sim iid(0, \Sigma)$ and $\Pi = \alpha\beta'$. The Π and Γ_i indicate the long-run and short-run dynamics, respectively: α summarizing the adjustment coefficients, and β the cointegrating vectors. Both α and β are $p \times r$ matrices, where *p* and *r* are the number of series and number of cointegrating vectors, respectively. The trace test using the ordered eigenvalues of Π (Johansen, 1988, 1991) is used (below) to decide the number of cointegration vectors.

Based on an estimated vector ECM, I consider two types of forecasts. The first are the *ex ante* (out-of-sample) forecasts, which are used to generate one step ahead forecast errors. Starting from January 3, 2000, the model is estimated and one-step-ahead forecasts generated recursively, every day through July 15, 2003. Also included in my recursive structure is an up-date on the number of cointegration vectors at each date. These forecasts and the one-step-ahead forecast errors are behind the *ex ante* innovations used below. The second type of forecast is from the *ex post* (within sample) forecast model, which is fitted using the entire sample period – January 2, 1995 to July 15, 2003.

I do not allow the number of cointegrating vectors to change recursively in generating these *ex post* forecasts, as I do in the case of *ex ante* forecasts (above). To compare results from both sets of innovations, I use only the innovations from January 3, 2000 to July 15, 2003 as *ex post* innovations.

2.3.1 DAGs (Directed Acyclical Graphs)

Here, I ask whether the contemporaneous causal structure from *ex ante* forecast innovations is consistent with the structure from the *ex post* forecast innovations. Furthermore, I inquire about similarities or differences in patterns of price transmission among stock values of ten sectors in the U.S. stock market. Both sets of innovations are obtained from the ECMs. In this case, the forecasted values from Vector ECM are assumed to reflect the market expectation on the stock market. These innovations are compared to innovations from the fit Vector ECM as shocks or new information to the market.

A DAG is a picture representing causal flow among a set of variables. The picture has variables that are connected by an arrow with the base of the arrow placed at the casual variable and the head at the effect variable; e.g. A → B signifies variable A causes variable B. Figures in this chapter contain no cycles. So, for example, I do not allow graphs of the form A → B→ A, or more extended paths where arrows lead away from a variable but eventually return to that same variable. Details on the now rich literature on DAGs can be found in Pearl (2000) and Spirtes, Glymour, and Scheines (2000). In this study, I use PC Algorithm (Spirtes, Glymour, and Scheines 2000) to build the casual structure based on observed correlations and partial correlations on measured innovations from the two types of innovations (ex ante and ex post).

Briefly, PC algorithm begins by forming a complete undirected graph. Every variable (innovations from returns in sector *i*) is connected to every other variable (innovations in each of the other nine sectors). That is, it begins with a picture in which each variable has a line (undirected) connecting it with every other variable. Lines are removed by considering the correlation and partial correlation between variables. That is to say, PC algorithm challenges each line by testing the (unconditional correlation) between the variables at its two end points ($\rho_{i,j} = 0$ where i and j refer to innovations from the ECM on categories (sectors) of the GICS aggregations). After all (zero-order) unconditional correlations are tested for zero values, PC tests any remaining edges (edges not removed at zero-order conditioning) via first order conditioning). That is, the test is that $\rho_{i,j|k} = 0$, where, here again, i and j refer to innovations from sector i, j, and k are innovations from another sector, $k \neq i, j$. After all possible first order conditioning tests are conducted, PC algorithm proceeds in testing all possible higher ordered conditionings, two, three, . . . , $n-2$ (eight). The null hypothesis in each test is that the conditional correlation is equal to zero. If I fail to reject the null in any of these tests, I remove the edge between the two variables whose correlation I are testing.

Here, Fisher's Z statistic is employed to test whether the unconditional or conditional correlation is or is not equal to zero. The form is the following:

$$z\left[\rho\left(i,j\,|\,k\right),n\right]=\left[\frac{1}{2}\sqrt{n-|\,k\,|-3}\right]\times\ln\left[\frac{\left|1+\rho\left(i,j\,|\,k\right)\right|}{\left|1-\rho\left(i,j\,|\,k\right)\right|}\right], \tag{2.2}$$

where $\rho\left(i,j\,|\,k\right)$ is the population correlation between i and j conditional on k, and n is the number of observations used to estimate the correlation. $|\,k\,|$ is the number of conditional variables in k. When i, j, and k are normally distributed and $\gamma\left(i,j\,|\,k\right)$ is the sample conditional correlation of *i*, *j* given *k*, the distribution of $z\left[\rho\left(i,j\,|\,k\right),n\right]-z\left[\gamma\left(i,j\,|\,k\right),n\right]$ is standard normal. The null hypothesis using Fisher's Z statistic is conditional population correlation equal to zero.

The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set). After exhausting all possible tests that zero and higher order correlations equal zero, one must direct edges that remain (no correlations are found to equal zero on these edges) based on the following rules: Edges are directed by considering triples X — Y — Z, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct edges between triples: X — Y — Z as X → Y ← Z if Y is not in the sepset of X and Z. If X → Y, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient Y — Z as Y → Z. If there is a directed path from X to Y, and an edge between X and Y, then direct (X — Y) as: X → Y. The PC algorithm is marketed as TETRAD II.

PC algorithm may not in all cases result in a directed acyclic graph, as it may not be possible to direct all edges. For example, if the underlying ("true") model connecting X,Y, and Z is a chain: X→Y→Z, TETRAD II may not find such directed flows, as the correlation patterns for such a model will not differ from those on a similar model with reversed flows: X←Y←Z. In such a case, PC algorithm will leave the triple X – Y – Z as undirected.

2.4 Empirical Results

Here, I present empirical results from an error correction model fit to the data described above. I carry-out standard innovation accounting analysis on the fit model based on a structural factorization of current period innovations.

2.4.1 Error Correction Representation

The maximum likelihood estimation procedure of Johansen (1991) is applied to construct a Vector ECM on daily stock market indices. A lag length of two periods on an underlying Vector Autogression (VAR) results in an vector ECM with one period on the short-run components of equation (2.1) (the Γ_i 's) using Schwarz loss on a levels VAR. Using this optimal lag, the test for cointegration should be preceded to support the

Vector ECM.[2] In addition, I consider the three-month U.S. Treasury Bill as an exogenous variable in this Vector ECM. [The corresponding coefficients on Treasury Bill are positive, indicating the market views the Treasury Bill as a substitute for equities, so that yesterday's % change of T-bill return rate affects the current % change of each stock return rate.]

The trace tests on cointegration, following Johansen and Juselius (1990), are used to test the sequential hypotheses of the existence of r cointegrating vectors. The null hypothesis is that the number of cointegrating vectors is r, against an alternative of k cointegrating relationships, where k is the number of endogenous variables (here $k = 10$), for r =0,…, $k-1$. The critical values are obtained from Osterwald-Lenum (1992). The trace test statistic is given as:

$$LR_{Trace}\left(r \mid k\right) = -T\sum_{j=r+1}^{k} \ln(1-\lambda_j)\,, \tag{2.3}$$

where T is the number of observations and λ_j is the j^{th} largest eigenvalue of Π in equation (2.1). We find four cointegrating vectors. See Table 2.2.

[2] I estimated another error correction model in which T-bill were allowed to be endogenous. Here, I found all coefficients associated with the effects of past stock indices on T-bill rates were not significantly different from zero at usual level of significance.

Table 2.2

Trace tests: from January 2, 1995 to July 15, 2003

Null Hypothesis on Cointegrating Vectors	Eigenvalue	Trace Statistic	Critical Value	
			5%	1%
$CV = 0$ **	0.040522	354.919	263.42	279.07
CV≤1**	0.031032	262.879	222.21	234.41
CV≤2 *	0.020379	192.739	182.82	196.08
CV≤3 *	0.018517	146.928	146.76	158.49
CV≤4	0.012906	105.343	114.90	124.75
CV≤5	0.010438	76.439	87.31	96.58
CV≤6	0.008869	53.091	62.99	70.05
CV≤7	0.007742	33.269	42.44	48.45
CV≤8	0.004069	15.977	25.32	30.45
CV≤9	0.003099	6.905	12.25	16.26

Note: A symbol CV is the number of cointegrating vectors. The asterisk(s) *(**) denotes rejection of the null hypothesis at the 5% (1%) significance level.

An error correction model, which incorporates these restrictions on Π of equation (2.1) is estimated on data from January 2, 1995 through July 15, 2003. Out-of-sample forecasts (*ex ante*) from this recursively up-dated vector ECM are used to generate out-of-sample forecast errors for the period January 3, 2000 through July 15, 2003. Within sample (*ex post*) fit errors are found using the observed data minus the fit values over the same period. Innovations from these two models are used to form *ex ante* (forecast) and *ex post* covariance matrices, $S_i, i = 1,2$. These are given as equation (2.4) and (2.5) (each element of equation (2.4) and (2.5) has been multiplied by 10^3 = 1000 to save space in presentation, so for example the 1,1 element of equation (2.4) should read 0.000302).

$$S_1 = \begin{array}{c} \begin{array}{cccccccccc} CD & CS & EN & FN & HC & ID & IT & MA & TS & UT \end{array} \\ \begin{bmatrix} .302 & & & & & & & & & \\ .089 & .148 & & & & & & & & \\ .106 & .069 & .262 & & & & & & & \\ .230 & .104 & .114 & .322 & & & & & & \\ .123 & .107 & .108 & .137 & .227 & & & & & \\ .231 & .095 & .117 & .234 & .136 & .270 & & & & \\ .319 & .034 & .093 & .290 & .113 & .307 & .825 & & & \\ .200 & .102 & .128 & .196 & .118 & .206 & .189 & .302 & & \\ .201 & .074 & .106 & .206 & .117 & .190 & .328 & .149 & .429 & \\ .099 & .072 & .133 & .131 & .097 & .114 & .103 & .103 & .108 & .279 \end{bmatrix} \end{array} \qquad (2.4)$$

$$S_1 = \begin{array}{c} \begin{array}{cccccccccc} CD & CS & EN & FN & HC & ID & IT & MA & TS & UT \end{array} \\ \begin{bmatrix} .289 & & & & & & & & & \\ .085 & .140 & & & & & & & & \\ .103 & .065 & .250 & & & & & & & \\ .221 & .100 & .111 & .309 & & & & & & \\ .118 & .101 & .104 & .132 & .217 & & & & & \\ .221 & .090 & .114 & .225 & .131 & .261 & & & & \\ .302 & .031 & .093 & .275 & .108 & .293 & .787 & & & \\ .191 & .098 & .123 & .188 & .112 & .198 & .179 & .288 & & \\ .201 & .071 & .104 & .198 & .113 & .183 & .314 & .142 & .416 & \\ .096 & .068 & .125 & .127 & .092 & .111 & .101 & .099 & .105 & .267 \end{bmatrix} \end{array} \qquad (2.5)$$

Here, S_1 is the estimate of Σ_1, the covariance matrix (lower triangular elements) from *ex ante* innovations, and S_2 is the estimate of Σ_2, the covariance matrix from *ex post* innovations. Notice that all elements of equation (2.5) are less than elements of equation (2.4), as I would expect when comparing within sample fit errors (equation (2.5)) with out of sample forecast errors (equation (2.4)). One may proceed to tests the equality of equation (2.4) and (2.5) following Box (1949). The equality between the two covariance matrices is tested using the mutivariate Box's M statistic (1949), which is a likelihood ratio test. The null hypothesis ($\Sigma_1 = \Sigma_2$) implying homogeneity of these matrices can not be rejected by Box's M test. Under the null hypothesis, the population covariance matrix Σ is $S = n^{-1}\sum n_i S_i$, and S_i under the alternative where S_i is the sample covariance matrix, where *i*=1 for *ex ante* forecasting innovations and 2 for *ex post* forecasting innovations. The test statistic is the following:

$$M = \gamma \sum (n_i - 1) \log \left| S_{u_i}^{-1} S_u \right| \tag{2.6}$$

where, $\gamma = 1 - \dfrac{2k^2 + 3k - 1}{6(k+1)(q-1)} \left(\sum \dfrac{1}{n_i - 1} - \dfrac{1}{n - q} \right)$ and S_{u_i} and S_u are unbiased estimators

$$S_u = \frac{n}{n-q} S \text{, and } S_{u_i} = \frac{n_i}{n_i - 1} S_i$$ [3]

The M statistic follows a χ^2 distribution having the degree of freedom, $k(k+1)(q-1)/2$ (=55) where k (=10) and q (=2) are the number of variables and the number of covariance matrices compared. n_1 and n_2 are both 922 in this case, the number of observations of *ex ante* and *ex post* forecasting innovations, where $n = n_1 + n_2$. In this

[3] This Box's M is adjusted using S_u and S_{u_i} because, from the likelihood ratio, $-2\log\lambda = n\log|S| - \sum n_i \log|S_i| = \sum n_i \log\left|S_i^{-1} S\right|$, if n_i is small, then this ratio gives too much weight to the contribution of S. See Mardia et al., pp. 140.

case, the test statistic value is 4.9467, which indicates that I fail to reject the null hypothesis at significant level of 0.01 and less, as the critical value is near 80. Hence, I cannot reject the null hypothesis that the covariance matrices are the same.

2.4.2 Directed Acyclic Graphs on Innovations

From the *ex ante* and *ex post* forecast innovations described above, two directed graphs are obtained from TETRAD II. These are given in Fig. 2.2. These graphs are identical.

Telecommunication and Utilities sectors are information "sinks" and the Information Technology sector is a "root cause" in terms of innovation discovery. The Financial sector causes the sectors directly related with the living standard: Consumer Discretionary, Consumer Staples, Telecommunication, and Utilities. The Financial sector is affected by the Industrial sector. Also the Consumer Staples sector (food and beverage industries) affects the Health Care sector, as well as Materials sector.[4] It was surprising to the authors that returns in the Health Care sector are a direct cause of returns in the Energy sector. Upon further investigation, I note Bernstein *et al.* (2003) summary of energy use: " … a larger health industry portion of the commercial sector increases energy use because hospitals and other health care facilities are relatively large energy users." (Bernstein *et al.*, 2003, page 28). Finally, returns in the Energy sector causes returns in Utilities and the Materials sectors.

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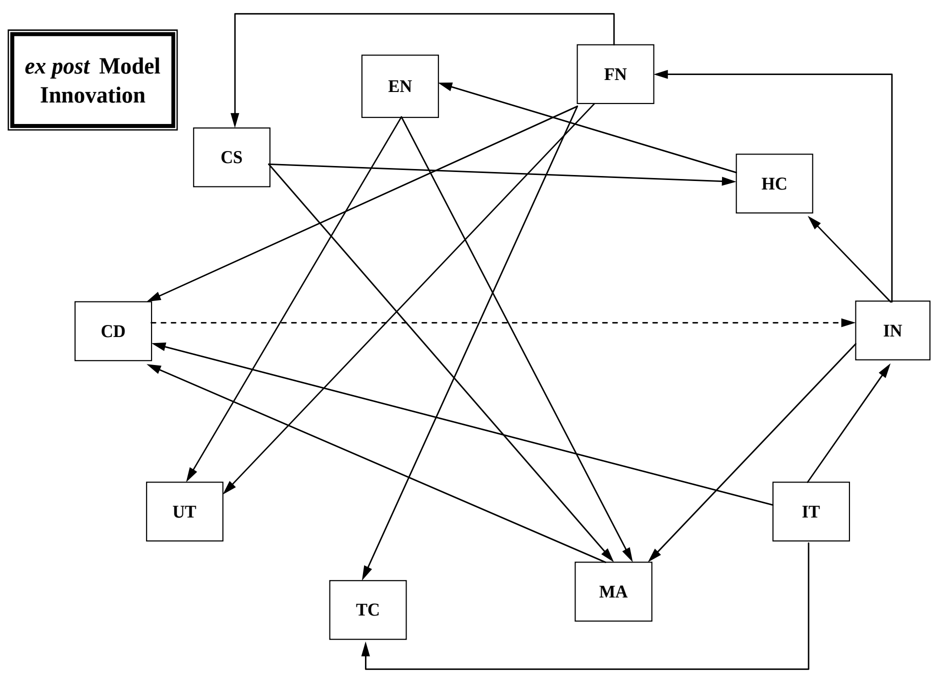
[4] The Material sector has Fertilizer, Agricultural and Other Chemical sub-industries.

TETRAD II cannot assign direction on the edge connecting Consumer Discretionary and Industrials. Recall from Table 2.1 that the Consumer Discretionary sector includes: Automobile & Components, Consumer durables & Apparel, Hotel, Restaurants & Leisure and Retailing. The Industrial sector includes: Capital Goods, Commercial Services & Supplies, and Transportation. If the assignment of causal flow is from



Note: The significant levels are 0.001 for the TETRAD II. The dotted line is not assigned a direction by TETRAD II. The abbreviations are CD (Consumer Discretionary), CS (Consumer Staples), FN(Financials), EN (Energy), HC (Health Care), IN (Industrials), IT(Information Technology), MA (Materials), TC (Telecommunication Services), and UT (Utilities).

Fig. 2.2. Graphical pattern from the market innovations in *ex ante* and *ex post* models.

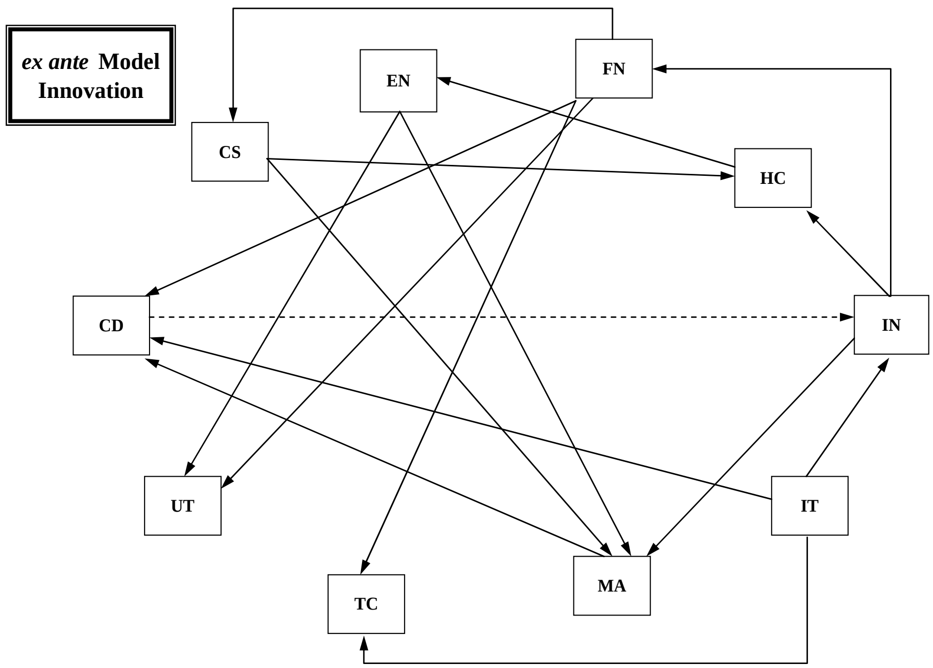


Fig. 2.2. (Continued).

Consumer Discretionary sector to the Industrials sector, this induces a cyclic graph, as Industrials cause Materials, which in turn cause Consumer Discretionary. I do not pursue direction on this edge further here, but leave it as unassigned. Finally, innovations in the Materials, Telecommunication, and Utilities sectors cause innovations in the Consumer Discretionary sector.

2.4.3 Innovation Accounting

Forecast error variance decompositions, based on a structural factorization using contemporaneous pattern from Fig. 2.2, are given in Table 2.3. The table entries show the percent variation of stock price in each sector that is due to innovations from itself and other sectors at several time horizons: short-horizon (0, 1, 2 days), mid-horizon (9 days), and long- horizon (29 days).[5]

The Consumer Discretionary sector appears to be dominated by itself (its previous innovations) and the Information Technology sector: 32% and 41%, respectively, at the zero-day horizon, and 22% and 36%, respectively, at the 29-day horizon. The Consumer Staples, Energy, and Utilities sectors are highly exogenous (about 77%, 79%, and 71%) in the short horizon, but less than 50% at the longer horizon (48%, 41%, and 42%). Here,the explanatory power of innovations of other sectors on these sectors increases at longer horizons. Note that the Consumer Staples sector, which includes food industries, is non-trivially affected by the Health Care sector including Biotechnology /Pharmaceuticals industries and the Industrials sector. The latter includes Transportation industries at a longer horizon. For all horizons, price variation in the Financials sector appears not to be exogenous at any horizon.

It is clear that the variation of Health Care sector is explained by Consumer Staples, Industrials, and Information Technology sectors. As in aggregate, these sectors explain about 40% of the variation in Health Care sector at any horizon. The Industrial sector

[5] As suggested above we do not assign a causal edge between Consumer discretionary and Industrials. The innovation accounting analysis presented here follows this omission. We have calculated results with the flow from Industrials to Consumer Discretionary that we will provide readers upon request. These (unreported) results are similar to results presented in Table 2.3.

appears to be dominated by the Information Technology sector (about 40%) at the short horizon, but the influence of the Health Care sector grows to about 12% at the longer horizon. The Information Technology sector appears to be the root cause, and therefore, is the most exogenous. Variation in Information Technology is explained by itself (75-100% at all horizons). The exogeneity of the Materials sector is also questionable over time since other sectors explain the variation of the Materials sector to a degree of about 50% at the short horizon, and over 70% at the 29-day horizon. The Telecommunication sector is closely related with the Information Technology sector. Variation in the Telecommunications sector is explained by itself (62-65%) and the Information Technology sector (24-28%). As I might expect, the Utilities sector is influenced by the Energy sector (11-13%) at a short horizon; Industrials and Information Technology sectors affect Utilities by 22% and 15%, respectively, at the 29-day horizon.

Table 2.3
Forecast error variance decompositions using structural factorization

Period	Standard Error	CD	CS	EN	FN	HC	IN	IT.	MA	TC	UT
Variance Decomposition of Consumer Discretionary sector:											
0	0.017	32.639	0.295	0.148	6.023	0.022	15.080	41.481	4.312	0.000	0.000
1	0.024	33.327	0.441	0.471	6.811	0.159	13.352	42.024	3.332	0.008	0.075
2	0.029	33.421	0.569	0.655	6.774	0.371	12.664	42.203	3.217	0.023	0.102
9	0.051	30.850	1.290	1.878	5.118	3.783	11.394	41.283	4.147	0.127	0.129
29	0.083	22.285	3.179	3.781	2.833	14.789	11.122	36.409	4.915	0.114	0.573
Variance Decomposition of Consumer Staples sector:											
0	0.012	0.000	77.365	0.000	8.414	0.000	8.267	5.955	0.000	0.000	0.000
1	0.016	0.003	77.144	0.179	7.681	0.556	10.726	3.264	0.004	0.441	0.003
2	0.020	0.005	75.712	0.216	7.373	0.971	12.555	2.428	0.003	0.736	0.002
9	0.037	0.033	67.499	0.226	6.027	3.021	18.978	2.079	0.002	1.998	0.137
29	0.065	0.085	48.619	0.319	3.556	9.263	27.330	4.491	0.151	4.454	1.733
Variance Decomposition of Energy sector:											
0	0.016	0.000	2.771	79.699	0.301	11.700	3.214	2.315	0.000	0.000	0.000
1	0.022	0.010	3.425	78.069	0.187	12.290	3.726	2.011	0.000	0.282	0.000
2	0.027	0.014	3.660	76.595	0.177	12.615	4.378	2.119	0.001	0.441	0.000
9	0.045	0.045	4.584	65.917	0.458	14.046	8.662	5.299	0.014	0.966	0.009
29	0.070	0.172	5.999	41.541	0.837	18.583	16.491	14.324	0.019	1.662	0.372
Variance Decomposition of Financials sector:											
0	0.018	0.000	0.000	0.000	37.170	0.000	36.522	26.307	0.000	0.000	0.000
1	0.025	0.024	0.120	0.151	37.139	0.348	35.945	26.188	0.000	0.084	0.000
2	0.030	0.046	0.216	0.342	36.365	0.843	35.985	25.994	0.001	0.207	0.001
9	0.050	0.241	0.823	2.202	28.700	6.396	35.544	24.677	0.044	1.260	0.112
29	0.082	0.464	2.362	5.480	14.607	20.512	31.133	20.596	0.487	2.983	1.376
Variance Decomposition of Health Care sector:											
0	0.015	0.000	13.650	0.000	1.484	57.631	15.832	11.404	0.000	0.000	0.000
1	0.022	0.014	13.568	0.165	1.467	59.333	16.143	8.882	0.019	0.329	0.080
2	0.027	0.022	13.463	0.238	1.462	59.368	16.755	8.031	0.054	0.437	0.170
9	0.048	0.025	12.786	0.550	1.456	55.564	19.969	7.432	0.756	0.281	1.182
29	0.082	0.037	11.310	1.628	1.021	46.580	23.040	8.366	3.328	0.107	4.583

Table 2.3 (*Continued*)

Period	Standard Error	CD	CS	EN	FN	HC	IN	IT.	MA	TC	UT
Variance Decomposition of Industrials sector:											
0	0.016	0.000	0.000	0.000	0.000	0.000	58.129	41.871	0.000	0.000	0.000
1	0.023	0.136	0.000	0.258	0.012	0.149	58.278	41.056	0.001	0.073	0.036
2	0.027	0.205	0.008	0.395	0.012	0.348	57.943	40.910	0.002	0.129	0.047
9	0.047	0.509	0.227	1.262	0.024	3.096	54.463	39.942	0.013	0.413	0.052
29	0.076	0.820	1.361	2.934	0.077	12.726	44.832	36.292	0.240	0.479	0.239
Variance Decomposition of Information Technology sector:											
0	0.028	0.000	0.000	0.000	0.000	0.000	0.000	100.000	0.000	0.000	0.000
1	0.039	0.206	0.042	0.229	0.050	0.002	0.637	98.633	0.083	0.004	0.113
2	0.048	0.285	0.073	0.392	0.102	0.011	1.050	97.807	0.113	0.003	0.165
9	0.083	0.295	0.356	1.867	0.497	1.213	2.918	92.169	0.250	0.081	0.354
29	0.137	0.134	1.413	5.287	0.959	6.405	5.969	75.946	0.306	2.278	1.303
Variance Decomposition of Materials sector:											
0	0.017	0.000	3.153	1.575	0.343	0.231	28.297	20.382	46.018	0.000	0.000
1	0.023	0.247	3.571	2.555	0.544	0.831	28.599	19.544	44.066	0.040	0.004
2	0.028	0.402	3.909	2.826	0.634	1.189	28.813	19.244	42.914	0.067	0.002
9	0.048	1.568	5.572	2.884	0.886	3.133	29.118	18.086	38.616	0.092	0.044
29	0.076	4.352	9.007	2.228	1.234	8.929	29.277	15.422	28.786	0.048	0.716
Variance Decomposition of Telecommunication sector:											
0	0.020	0.000	0.000	0.000	4.657	0.000	4.575	28.741	0.000	62.027	0.000
1	0.029	0.013	0.042	0.034	4.131	0.086	3.549	28.691	0.022	63.427	0.005
2	0.035	0.026	0.075	0.098	3.740	0.210	3.074	28.521	0.034	64.217	0.005
9	0.061	0.148	0.291	0.998	2.178	1.739	1.732	27.233	0.113	65.564	0.003
29	0.100	0.356	0.862	3.439	0.861	5.839	0.703	24.575	0.393	62.910	0.061
Variance Decomposition of Utilities sector:											
0	0.016	0.000	0.397	11.418	4.158	1.676	6.219	4.479	0.000	0.000	71.653
1	0.023	0.001	0.537	12.871	3.620	2.346	7.267	4.524	0.062	0.060	68.711
2	0.028	0.003	0.533	13.077	3.426	2.575	8.232	4.741	0.119	0.092	67.201
9	0.049	0.033	0.284	11.248	2.983	2.922	13.695	7.864	0.778	0.065	60.128
29	0.079	0.134	0.207	8.154	1.704	5.082	22.536	15.974	3.759	0.086	42.363

Note: The level VAR, derived from the estimated error correction model, is applied to obtain this Variance Decomposition using a DAG-based structural factorization.
The abbreviations are CD (Consumer Discretionary), CS (Consumer Staples), FN(Financials), EN (Energy), HC (Health care), IN (Industrials), IT(Information Technology), MA (Materials), TC (Telecommunication Services), and UT (Utilities).

2.5 Conclusion

This paper shows the relationships among 10 sectors in the stock market in terms of price transmission using an error correction model. I study both *ex ante* and *ex post* innovations for modeling causal flows in contemporaneous time. I demonstrate using TETRAD II that the two methods for calculating innovations (within-sample fit versus out-of-sample forecasts) result in the same causal graph on innovations. Forecast error variance decompositions based on this graph are studied to provide a summary of the dynamic flow of information among the ten sectors. My results indicate the Information Technology sector is highly exogenous. Further, Information Technology, Industrials, and Health Care sectors have considerable influences on other sectors of the U.S. equities market.

Clearly, researchers' efforts are less complicated if within-sample-fit gives the same result as out-of-sample-forecast in the study of contemporaneous innovations. Here, I demonstrate that this is the case for recent data on U.S. equity aggregates. Whether this same result holds in other cases I have nothing to say. If further research efforts are able to demonstrate similar results, researchers may place more confidence in the less complicated, within-sample-fit, procedures.

CHAPTER III

MODELING REITS' DYNAMICS UNDER STRUCTURAL CHANGE WITH UNKNOWN BREAK POINTS

3.1 Introduction

In the U.S., Real Estate Investment Trusts (REITs) have taken an important role in real estate investment since the creation of REITs by Congress in the 1960s. REITs have supported the indirect investment or finance of the real estate sector with Mortgage-backed Securities (MBS). A company which qualifies as a REIT is permitted to deduct dividends paid to its shareholders from its corporate taxable income. Most important, REITs are legally required to distribute at least 90% of their taxable income to shareholders annually in the form of dividends, thus differentiating REITs from other stock assets. As the REITs industry has developed, it has become an important alternative investment tool for a wealth-building portfolio, compared to more traditional stock market investments. According to the National Association of Real Estate Investment Trusts (NAREIT) at 2004, there are approximately 200 publicly traded REITs in the U.S. today. And, recently, the ratio of REITs to S&P 500 has increased to more than 19% in 2003 compared to less than 10% in 1983, in terms of market capitalization[6]. As the market size of REITs increases, the positive relationship between returns on REITs and stock appears to be weak. This apparent relationship will be investigated in this chapter. The shares of these companies are traded on major stock exchanges, which set them apart from traditional real estate companies. Additionally, no more than 50% of the shares can be held by five or fewer individuals during the last half of each taxable year. Further, at least 75% of the total investment assets must be in real estate related entities.

During the first three years of the 2000s, an inverse relationship persisted between returns on REITs and returns on the S&P 500. REITs jumped 63% in value from the end of 1999 to the beginning of 2004, compared to a 23% drop in the S&P 500 index during the same period. Interest rates also decreased during the period. Investors consider that stocks, REITs, and other assets including bonds are other forms of investments. If the Federal Reserve raises interest rates, then the return on bonds increases, making bonds more attractive relative to stock and REITs. This causes a decrease in demand for stocks and REITs. While this prediction implies that both types of returns would increase in response to a decrease in interest rates, the two types of returns show different movements during the first three years in the 2000s. There has been no research to explain the inconsistency of these movements with theoretical expectations. Here, a multivariate econometric model is set up to explain these different movements of returns on stocks and REITs.

[6] For S&P 500, the market capitalization value is based on year end total indexed assets (Standard & Poor's, "Annual Survey of S&P Indexed Asset", 2003d). And for REITs, it is equity market capitalization outstanding (NAREIT, "Annual Market Capitalization", 2004).

So far, many have studied the dynamics of financial markets using macroeconomic variable, but no one focuses on recent different movement of returns on stocks and REITs. Chen, Roll, and Ross (1986) were the first to explore and focus on the influential relationships between financial market and economic state variables. They found that the relationship between financial markets and the macroeconomy is not unidirectional. McCue and Kling (1994) found that a shock to nominal interest rates has a significant negative effect on the real estate return using VAR over 1971 to 1991. However, shocks to other macroeconomic variables (output and investment) have little explanatory power on movements in real estate returns. Ewing and Payne (2005) have studied the magnitude and persistence of unanticipated changes in four macroeconomic variables (monetary policy, real output, default risk premium, and inflation) on REIT returns using a general impulse response (Koop *et al*. (1996), and Perasan *et al.* (1998)). Payne (2003) extends the Ewing and Payne (2005) model using three classifications of REITs: equity, mortgage, and hybrid types of REITs. The three types of REITs respond in a similar manner to shocks in macroeconomic variables, with the exceptions of inflation and default risk.

In addition to the comprehensive studies mentioned above, more direct studies of the relationship between the real estate and the stock market were published in the 1990s. Since then, many researchers have noted that there are significant features of market integration between the two. Gyourko and Keim (1992) demonstrate that the return on REITs is affected by the return of S&P 500 investments using a regression model. Peterson and Hsieh (1997) also find that equity REITs are significantly related to stock portfolios in terms of risk premiums and return rates using the five-factor model of Fama and French (1993). Okunev *et al*. (2000) support these studies by finding a unidirectional causal relationship from stock market returns to real estate returns.

These studies of the relationship between real estate and the stock market have all been carried out assuming there has been no structural change. It implies that the relationship between REITs and related variables is unchanging or stable through time. It is of general interest if the empirical relationship between REITs and other related variables has changed. Also, some researches have considered the possibility of structural break(s) with policy/economic changes or economic performances in modeling returns on REITs (Ewing and Payne (2005), Payne (2003), Chui *et al.* (2003) Okunev *et al.* (2000)). However, their studies were not supported by comprehensive and formal tests for multiple structural break(s) with unknown break point(s).

In addition to the incorrect handling of potential structural change, existing studies of the dynamics for REITs do not pursue contemporaneous causal relationship among the variables considered. Ewing and Payne (2005) and Payne (2003) use predetermined contemporaneous causations, a generalized impulse response analysis, to study the dynamics of REITs including other macroeconomic variables. In this study, empirical causal relationships using Directed Acyclical Graph (DAG) are investigated, and those relationships are imposed in an econometric model for dynamics as contemporaneous causal relationships.

The objective in chapter III is to build an empirical econometric model, as a successor of Chen *et al.* (1986), to provide an explanation of recent differences in the dynamics of returns on REITs and equities against decreasing interest rates, which have not been addressed in previous studies. At the same time, a structural break test applied to the REITs model will be included to investigate the possible existence of structural break(s) in REITs, which was just assumed or was searched by non-comprehensive tests in previous studies (Okunev *et al.* (2000), Ewing and Payne (2005), Payne (2003), and Chui *et al.* (2003)). Specially, the Sup LM test by Andrews (1993) will be applied to investigate the possible existence of (multiple) structural break(s) with unknown point(s). If the test result supports the existence of structural change, detection of change point(s) and the comparison of underlying dynamics will be studied to better understand implied differences.

3.2 Empirical Methodologies

This chapter studies the innovation accounting of REITs return and stock market returns and other macroeconomic variables using the vector autoregression (VAR) model as Chen *et al.* (1987) did. This chapter offers two robust methodologies to further the existing research. First, a hypothesis testing for a structural break with an unknown break point is considered to implement a uniform sample period. For model reliability, the empirical econometric model should have stable parameters over the sample period, which is known as a case of no structural break. Well-known hypothesis tests for structural change (the Chow test and other traditional tests) exhibit nuisance parameter problems in the case of an unknown break point. The problem with the nuisance parameter arises when the observed data depends on the nuisance parameter only under the null hypothesis but not under the alternative hypothesis. Davis (1977, 1987) suggests that a structural change test with an unknown change point does not fit into the standard testing framework. Seo (1998) suggests that conventional LM statistic is not appropriate in the case of an unknown break point because the classical optimality theory does not hold due to the nuisance parameter problem[7]. Therefore, this chapter uses the Sup LM test suggested by Andrews (1993) for a structural break test with an unknown break point. This test is the general method and has asymptotic distributions for a structural break test with an unknown break point. If the existence of a structural break is identified, the estimation of the break point is pursued using the work of Bai (1994, 1997) and Saikkonen *et al.* (2004).

For a specific empirical model, a parameter stability test and a break detection analysis allow researchers to find an appropriate sample period. Parameter instability is often called a structural break or change. If a structural break exists over a sample period, empirical estimation using the entire sample will cease to provide reliable results and hypothesis testing will no longer be valid. Hendry (1997) and Clements and Hendry (1999) argue that many major failures of economic forecasts are due to the structural breaks, which are represented by parameter instability. Especially since the monetary policy change at the end of 1970s, there have been major policy and economic changes in U.S., such as the tax cut in 1981, Tax Reform in 1986, the stock market meltdown in 1987. According to the previous research, structural breaks coinciding with

[7] That is, the conventional likelihood based LM test statistic has a nonstandard distribution in this case.

policy/economic changes or economic performances have affected returns on REITs. Ewing and Payne (2005) and Payne (2003) assume a predetermined structural break to study REITs dynamics. The break is placed at the beginning of the 1980s, which is known as the period after the twin recessions. Chui (2003) imposes two structural breaks, in 1983 and 1990, based on the performance of REITs to examine momentum effects on REITs. However, these studies do not depend on a formal hypothesis test for the structural break. Although Okunev *et al*. (2000) study the causal relationship between real estate and stock markets and apply the structural break test used in Zivot and Andrews (1992), the test considers only trend/fundamental stationary in unit root; it does not consider a comprehensive test of stability for parameters and possible existence of (multiple) structural break(s) in the econometric model. They detect a structural break point in August 1989. In this chapter, the Sup LM test as the multivariate structural break test with unknown break point is applied to investigate the possible existence of (multiple) structural break(s) in this REITs model.

The second contribution of this chapter is to apply the Bernanke decomposition on innovations using Directed Acyclical Graph (DAG) for REITs dynamics. Other studies investigating REITs have not used DAGs as an analytic tool. Because economic theory cannot explain all causal relationships, DAG analysis will provide useful information about contemporaneous causations in this chapter. DAG analysis allows us to search the contemporaneous causal structure among innovation series from the VAR. The causal structure searched using DAG will be imposed on the innovations in the VAR model. This allows application of the Bernanke decomposition without using subjective judgment. This contemporaneous relationship is an over-identified restriction to orthogonalize the unexpected shocks in the VAR[8].

3.2.1 Structural Break Test

In this REITs model using VAR, curiosity arises concerning whether there might be either a single break or multiple break points. Possible candidates for breaks are a monetary policy change in the end of the 1970s, a tax cut in 1981, the end of the twin recessions in 1982, the Tax Reform Act of 1986, the stock market meltdown of 1987, and the savings and loan crisis in the late 1980s. The structural break test is often called a parameter instability test because the test is based on a discontinuity in parameter values. Andrews (1993) suggests using the generalized structural break test with unknown break point to test if an effective break exists in the sample period being considered. The basic time series model is as following:

$$y_t = x_t \beta_t + x_t d_t \delta + \varepsilon_t , \tag{3.1}$$

where $d_t = 1$ if $t > T^*$, and T^* is the possible break point.

When the time series y_t is explained by x_t in the above equation, the focus is whether the parameter β_t is stationary or non-stationary over time. Based on this idea, the null

[8] In the univariate model, the innovation series should not have serial correlation. Similarly, there should not be any correlation among the innovation series in the multivariate model. The latter case is called orthogonalization.

hypothesis assumes there is no break, $H_0 : \delta = 0$. For convenience, a possible break point (T^*) is considered as a portion (τ) of total observations (n). Hence, the alternative expression of null hypothesis is expressed by:

$$
\begin{aligned}
H_{1T}(\pi) : \beta_t &= \beta_1(\tau) \quad for\ t = 1,\ldots,n\tau \\
&= \beta_2(\tau) \quad for\ t = n\tau + 1,\ldots,n
\end{aligned}
\tag{3.2}
$$

If the break (τ) is known, the traditional maximum likelihood based tests (Wald, LR, and LM) using a dummy variable, or, alternatively, other stylized parameter instability tests such as CHOW, CUSUM, or CUSUM square can be used to test significance of the break. However, because τ appears under the alternative only, in the case of an unknown break point, a nuisance parameter problem arises. A possible break (τ) is assumed to be between 0.15 and 0.85 for the sustainability of the model. After each Lagrange Multiplier (LM) statistic is calculated and saved at every possible break (τ), the maximum LM statistic becomes the Sup LM statistic for the structural break test.

Because the test statistic has a non-standard distribution, Andrews (1993) examines and reports asymptotic critical values over various numbers of restrictions, up to 20. The calculation of the asymptotic distribution starts to find the limit process ($= Q_p(\tau)$) in LM test statistic. For any fixed τ, $Q_p(\tau)$ has a chi-square distribution with p degree(s) of freedom (i.e. the number of parameter restrictions). Once approximating the distribution of supremum $Q_p(\tau)$ over $\tau = [\tau_0, 1-\tau_0]$, the distribution of Sup $Q_p(\tau)$ is simulated using the Monte Carlo methods to find the asymptotic distribution. Because this study applies seven endogenous variables including a constant in the VAR, asymptotic distributions for 56 space (=7×8) parameter restrictions, i.e. degree of freedom in the test, are simulated over τ =[0.15, 0.85].[9]

3.2.2 Detection of Break Point Including Multiple Break Issue

If Sup LM test result supports existence of structural change in a given sample period, a specific break point needs to be found, Bai (1994, 1997). From equation (3.1), the sum of squared residuals ($S_n(k)$) for all possible breaks are estimated. Then the change point, $T^* = \tau^* n$, is defined as

$$T^* = \arg \underset{\tau n \leq k \leq (1-\tau) n}{Min} S_n(k) \tag{3.3}$$

Even if the first structural break point is identified and detected, it is still not known whether more than one break exists. When the existence of multiple breaks is suspected, it is necessary to repeat the above procedures—the Sup LM test and detection of break point—over the sub-sample groups.

[9] See Andrews (1993) for details.

3.2.3 DAG Analysis for Orthogonality

An issue of orthogonality among the innovations arises in the VAR after a consistent sample period is identified through the structural break test. When the innovation series are not orthogonal, contemporaneous relationships exist among them. To get accurate and consistent innovation accounting in the VAR, the contemporaneous causal relationships should be imbedded for orthogonal innovations before innovation accounting analysis.

Because the Cholesky ordering imposes just-identified restrictions, various methods to find orthogonal innovations have been applied. Bernanke (1986) and Sims (1986) provide over-identified restrictions based on the theoretical background among the variables and relax Cholesky ordering. Koop *et al.* (1996) and Perasan *et al.* (1998) suggest a generalized impulse response function method. The Generalized Impulse Response Function from an innovation to the *j-th* variable is derived by applying a variable specific Cholesky factor computed with the *j-th* variable at the top of the Cholesky ordering. Swanson and Granger (1997) recommend using Directed Acyclical Graph (DAG).

When a single structural break over the sample period exists, two covariance matrices for the sub-sample periods—before and after the break—can be tested using either the Box (1949) or Jennrich (1970) method, which both examine homogeneity of more than two covariance matrices via a chi-square test. The existence of a single structural break generates two covariance matrices regarding VAR innovations. In this case, both covariance matrices can be compared through Box (1949) and Jennrich (1970) tests. If the null (homogeneity) is rejected, then both covariances are significantly different from each other. This provides evidence that a causal diagram from the covariance is different from that of any other covariance matrix.

Two popular algorithms are considered to search for patterns in the DAG. The first candidate is the PC algorithm (Pearl 2000) that assesses particular independence and conditional independence using the null hypothesis test. Harwood & Scheines (2002) and Heckerman *et al.* (1999) call the PC algorithm a "constraint-based search." The second candidate is the Greedy Equivalence Search (GES), which is a score-based search algorithm. Dash and Drunzdzel (1999) provide a constraint-based search that is relatively speedy but has two well-known weaknesses. One arises from the treatment of latent variables. The constraint-based search tends to detect the causal relationship as a bi-directed arrow when a latent variable exists. The other weakness is an instability problem over the sample size. Bayesian methods can be applied even with very little data where conditional independence tests are likely to break down (Dash *et al.* 1999).

Because the GES algorithm ensures generating better-fitting DAGs under small sample size, the GES algorithm is more appropriate in this study than the constraint-based algorithm. Additionally Silvia *et al.* (2005) report that score-based approaches for learning the structure of Bayesian networks, such as GES (Chickering, 2002b), are usually more accurate than a constraint-based search with small to medium sized samples. Haughton (1988) suggests that the Bayesian scoring criterion is asymptotically consistent.

By definition, Bayesian Information Criterion (BIC) is used in model selection to select the best model from a set of plausible models. One model is better than another model if it has a smaller BIC value. BIC is based on integrated likelihood in Bayesian theory. If the complexity of the true model does not increase with the size of the data set, BIC can be a preferred criterion. Here, a GES algorithm using the Bayesian score is recommended in a model having relatively few observations, i.e. about 100 before the break and less than 200 after the break. With the Greedy Equivalence Search (GES), or a score search, an algorithm detects the causal pattern using the following systematic search algorithm. Starting with an undirected DAG, the two-phase algorithm is applied. In the first phase, the Forward Equivalence Search phase calculates the goodness of fit among all equivalence classes with a single additional edge (acyclic) and takes the class having the highest score. This procedure is repeated until no improvements can be made to the score. In this phase, the algorithm finds a comprehensive optimal model that includes the most best-fit models. The Backward Equivalence Search phase starts with the result of the first phase. Here, it repeatedly searches among equivalent classes with a single edge less and takes the graph with the highest Bayesian Score until no improvement can be made. This means that the best fit model is chosen among the structural equation models using the innovations from VAR.

For the Bayesian Score, a chi-square test (Bollen 1989) and a modified Schwarz Information Criterion (Haigh and Bessler, 2004) can be applied. First, a chi-square test statistics is given as $-2 \times \ln(L_0 / L_1)$, where L_0 and L_1 are the restricted likelihood under the null and the unrestricted likelihood values, respectively. It follows the chi-square distribution with degrees of freedom based on the number of restrictions imposed for the null hypothesis. According to Bollen (1989), the chi-square test statistic is equal to $(N-1)F_{ML}$, where F_{ML} is a fit function and should be minimized under the null, $H_0 : \Sigma = \hat{\Sigma}(\theta)$, which implies that the over-identifying restrictions imposed on the model are correct. The fit function (F_{ML}) is following:

$$F_{ML} = \ln\left|\hat{\Sigma}(\theta)\right| + tr(\hat{\Sigma}(\theta)^{-1} S) - \ln|S| - p \tag{3.4}$$

where, $\hat{\Sigma}(\theta)$ is an implied covariance matrix by the model, and θ contains coefficients and other parameter values. The symbols S and p represent the sample covariance matrix and the number of observed variables in the model, respectively. Finally, an asymptotic distribution of $(N-1)F_{ML}$ is a chi-square distribution with the degree of freedom $0.5*(p)\times(p+1)-r$, where r is the number of free parameter. For calculating r, the number of innovation series as well as the number of coefficients estimated in the structural equation model is included. For details, see Bollen (1989).

Second, a modified Schwarz Information Criterion (SL^M) is the following:

$$SL^M = \ln\left(\left|\Sigma^*\right|\right) + k \times \frac{\ln(T)}{T} \tag{3.5}$$

where, Σ^* is a diagonal matrix from variance-covariance matrix from innovations of VAR, and $|\Sigma^*|$ indicates a determinant of Σ^*.

Among the various methodologies for Bayesian score calculations [10], two methodologies—a chi-square test and a newly modified BIC— are chosen. The result provides the chi-square statistics calculated by TETRAD IV and the modified SIC we calculated to find the best fit model candidate.

3.3 Data

The following variables use monthly data from December 1971 through November 2004 and are applied in empirical work. The REITs return rate (RT) is calculated by the log difference in the 'Total' classification REITs index provided by the National Association of Real Estate Investment Trust (NAREIT). The stock return rate (SP) is obtained from the log difference of the S&P 500 index. Inflation (INF) is calculated using the growth rate of the consumer price index. A log difference of an industrial production index (IP) implies an output growth rate. The term structure (or term spread) of interest rate (TERM) is classified as the difference between the 10 year U.S. Treasury bond rate and the 1 month U.S. Treasury bill rate. The default risk (RISK) is defined as credit spread risk, the difference between Baa and Aaa corporate bond rates. The 1 month rate is also calculated using the 3 month U.S. Treasury bill rate. Because four week U.S. Treasury bill rates are available after the July 2001, the 3 month Treasury bill

[10] For more studies, refer Hipp and Bollen (2005), Schermelleh-Engel and Moosbrugger (2003), and Widerman (2003).

rate which is annualized is divided by 12 in order to proxy as a monthly rate. The first difference of this 1 month rate is notated by RATE. The use of logarithmic transformations on RT, SP, INF, and IP follows the literatures, Ewing and Payne (2005) and Payne (2003). The transformation is essentially stabilizes the variables on the series.

The REITs returns, S&P 500 returns, growth rate of industrial production, inflation, term spread and default risk are all integrated of order zero found by the unit root test. The interest rate, however, is transformed by differencing using its lagged value to be integrated of order zero.

3.4 Empirical Results

3.4.1 Structural Break

Using the entire period, January 1972 to November 2004, the Sup LM test for the structural break with an unknown break point is examined. For the test, 56 restrictions[11] are imposed to consider structural change in all coefficients of the VAR. The results are reported in Table 3.1. Because the test statistics of Sup LM, 87.66, is greater than 90% of the asymptotic distribution[12] generated, there is a structural break in the system. Following the Bai (1994, 1997) method, the break point (T^*) is found at October 1980 (i.e. new regime starts in November 1980). Then, the possible existence of multiple

[11] The number of restrictions, 56, is based on the number of all coefficients in the VAR – seven endogenous variables and a constant.

[12] Under a given $\tau = 0.15$, the asymptotic distributions of test are estimated by 86.42, 90.91, and 98.99 at 90%, 95%, and 99%.

Table 3.1
Structural break results

	Sample period	Sup LM statistics[b]	τ^b	# of restriction[c]	Critical value[d] 90%	95%	99%	Break point detection
Model 1[a]	Dec. 1971 - Nov. 2004	87.66	0.15	56	86.52	90.91	98.99	Oct. 1980
	Sub sample periods							
	(1) Nov. 1980 - Nov. 2004	84.88	0.15	56	86.52	90.91	98.99	No break
	(2) Dec. 1971 – Oct. 1980	68.65	0.30	56	86.52	90.91	98.99	No break
Model 2[*]	Dec. 1971 - Nov. 2004	33.39	0.15	12	27.08	29.61	34.56	Feb. 1980

Note:
a: Model 1 is a vector autoregressive using all variables, REITs return rates, stock return rates, industrial production growth rate , inflation rates, term spread, default risk, and interest rate changes. And Model 2 is vector autoregressive using REITs return rates, stock return rates, and interest rate changes, only.
b: Andrews (1993)
c: It is a total number of explanatory variables in the VAR.
d: In model 1, we simulate the critical value using Andrews (1993) for p=56.
The critical values of Model 2 having p=12 are replicated from Andrews (1993)

structural breaks is investigated using application of the structural break test for each sub-sample period, i.e. before and after break periods. By the tests for each sub-sample period,[13] the Sup LM statistic is less than the critical value at 90% of the asymptotic distribution. The single break point estimated in this research implies there are no other effective structural breaks[14]. One of the most plausible reasons for the structural break is the monetary policy change conducted by P. Volker, a Chairman of the Federal Reserve Bank from August 1979 to August 1987. His responsibility for ending the inflation crisis of the early 1980s was achieved by controlling the money supply via an interest rate increase. Basically, the break is due to the change in U.S. monetary policy. After Paul Volker is appointed in August 1979, monetary policy was designed to reduce market uncertainty through mitigating high inflation rates. The U.S. economy system began to adapt its behavior to the new monetary policy and the accommodated behavior began to show in November 1980. Also, through an additional structural break test, applied to three endogenous variables, rather than seven endogenous variables, the result strongly support the existence of structural change between two assets—stock and REITs—returns and interest rates (see model 2 in Table 3.1).

The tax policy changes- the Tax Cut of 1981 and the Tax Reform Act of 1986- do not account for structural breaks, but monetary policy does. It implies that there is no distortion in relationships among risky assets and macroeconomic variables from the tax policy changes.

[13] A sub-sample 1 (before the break, December 1971-October 1980) and a sub sample 2 (after the break, November 1980-November 2004)

[14] As other possible structural breaks, the Tax Cut of 1981, the Tax Reform Act of 1986, the stock market meltdown of 1987, and the savings and loan crisis in late 1980s are considered but not effective.

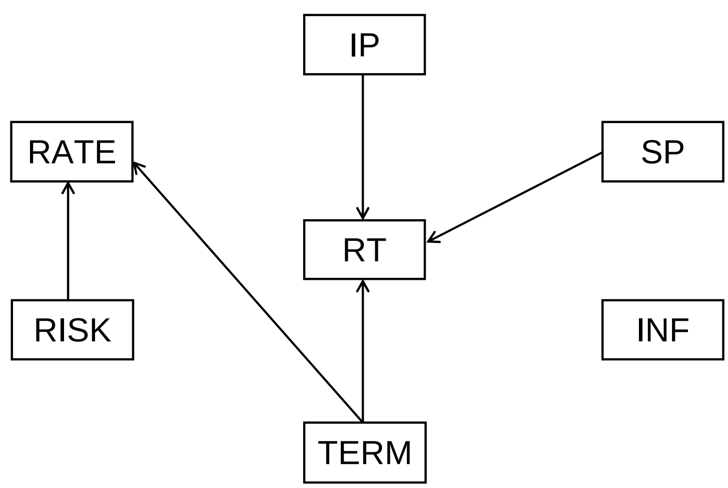
3.4.2 Two-periods Analysis

Here, the entire sample period is divided into two sub-sample groups—pre-break period (January 1972−October 1980) and post-break period (November 1980−November 2004) —for the following analysis. It means that structural break is considered in this two-periods analysis.

3.4.2.1 DAG

In each period, contemporaneous causations using the GES algorithm are estimated and drawn in Fig. 3.1.

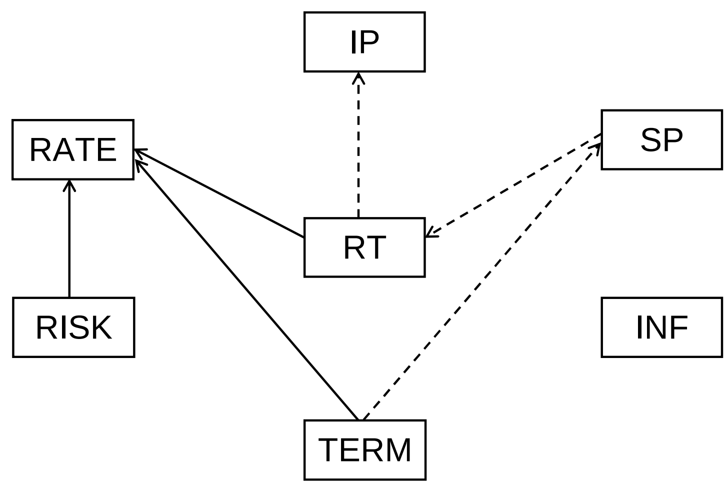
(A) Pre-break period (January 1972-October 1980)



Note:The abbreviations are RT (REITs returns rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

Fig. 3.1. Contemporaneous causal diagrams.

(B) Post-break period (November 1980 – November 2004)



(C) All sample period

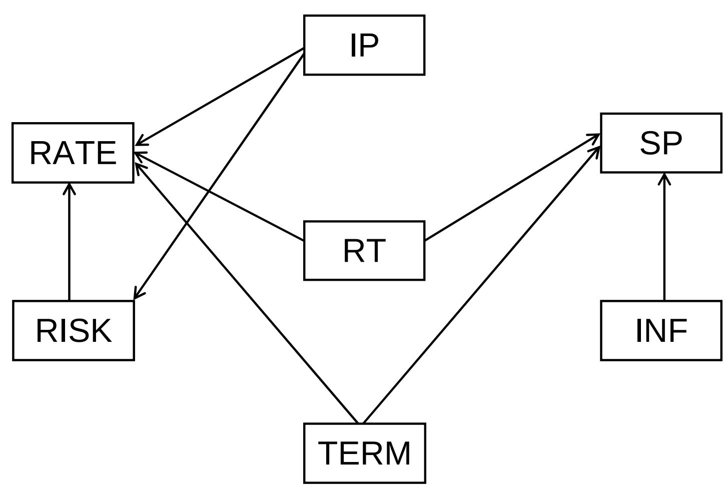
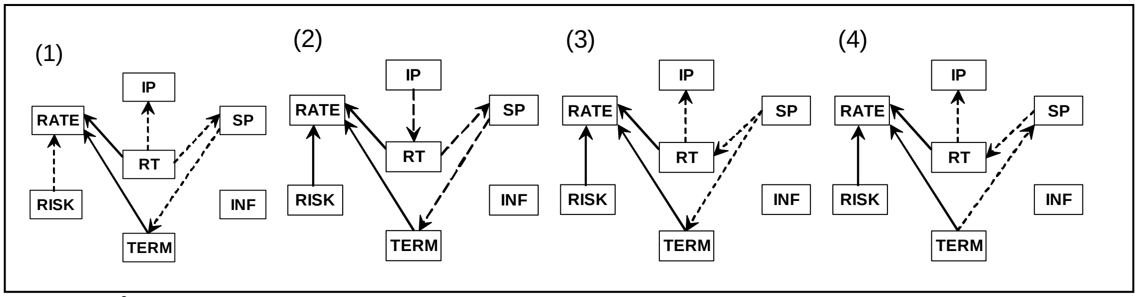


Fig. 3.1. (*Continued*).

Most importantly, three common features in both periods are identified from the graphical diagrams for contemporaneous causation. First, the common contemporaneous causal relations in both periods are: (i) the effect on REITs of a shock in stock return, (ii) the effect on interest rate change of a shock in term spread of interest rates and default risk. Both are reasonable because REITs are traded on the stock exchanges and the short-term interest rates can be explained as an adjustment process based on term structure and default risk spread information. Second, the shock in inflation is instantaneously independent of other variables in both periods. Third, term spread and default risk can be considered contemporaneous root causes in both periods.

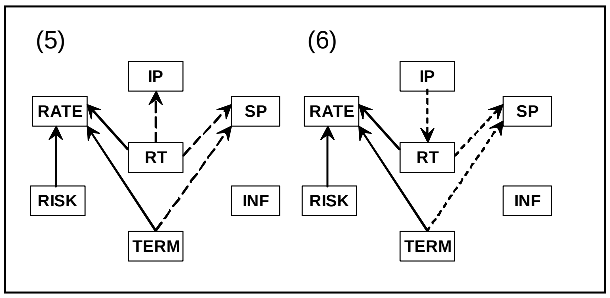
However, one of the most important differences arises with respect to the causality regarding real estate return (RT) between pre- and post-break periods. Real estate has a more causal ability in the post-break period compared to that in the pre-break period. The GES algorithm finds a new directed edge from a real estate returns to interest rate change during the post-break period. Also, even if three undirected edges (RT-IP, SP-RT, and TERM-SP) are found, one of the most plausible causations shows that RT appears to cause the growth rate of industrial production contemporaneously. Here, I discuss the procedure of how to assign ambiguous directions among undirected edges. First, the number of possible candidates can be reduced using a concept of the equivalent class. Then, a certain direction will be assigned from among narrowed possibilities arrived at using existing theory and empirical research.

(A) Equivalent class 1



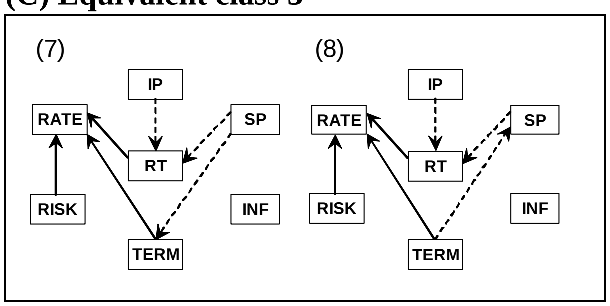
$\chi^2_{df=15} = 27.4571$, SIC = -86.9465

(B) Equivalent class 2



$\chi^2_{df=15} = 28.6904$, SIC = -86.9414

(C) Equivalent class 3



$\chi^2_{df=15} = 30.2421$, SIC = -86.9360

Note: The abbreviations are RT (REITs returns rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

Fig. 3.2. Equivalent classes in the post-break period.

Initially, a GES algorithm has no more explanation to assign directed edges in three undetermined relationships, RT-IP, SP-RT, and TERM-SP. Because there are three undirected edges, there are eight possible cases of directed causal relationships. These possible cases can be segregated into equivalent classes. The equivalence is conceptually defined in two ways: distributionally equivalent and independence equivalent. When two DAGs exist, both are distributionally equivalent if they have the same probability distribution. In contrast, both models are independence equivalent if they have same independence condition such as d-separation (Pearl 2000). Generally, they are not both the same, but independence equivalence accompanies the distributional equivalence in the case of a multivariate Gaussian model15 which this paper applies (Chickering *et al*. 2002, Chickering 2002b, and Spirtes 2005).

Among the three equivalent classes in Fig. 3.2, the first panel—having four equivalent DAGs—is the best with respect to a Bayesian Information Criteria (BIC), i.e. chi-square test statistics and Schwarz Information Criterion. Each DAG in the first equivalent class guarantees the optimality based on BIC[16], but there is still no agreement about contemporaneous causal relationships among RT, SP, IP and TERM. To pick one out of the four equivalent DAGs, the relationship between stock return and term structure of interest rate is the focus. A number of studies exist which explain the movement of the stock market. Keim *et al.* (1986) and Fama *et al.* (1989) suggest a term spread can be an explanatory variable at the business cycle level to predict the stock

[15] It is possible in the model having discrete distribution without latent variables

[16] Because GES algorithm has attained the optimal BIC, any other improvement in the first equivalent class is not available from the second step of GES algorithm.

market. Campbell (1987) shows that term spread of interest rate predicts excess stock returns and excess returns on bills and bond. Also, Avramov (2002) and Avramov *et al.* (2006) provide that a term spread is useful to forecast a stock return. In addition to the studies for significant linkage between real estate and real output (Goodhart *et al.* 2000, 2002), Mcdonald (1996) argues real estate can be considered an input into the commercial and industrial production processes. As mentioned, the stock market has an effect on the real estate industry. Hence, model (4) at equivalent class 1 (see Fig. 3.2) can be considered one of the most appropriate DAGs for the post-break period.

The estimated variance-covariance matrices (lower triangular) of innovations[17] from VARs in pre- and post-break periods are given as the following Σ_1 and Σ_2:

$$\begin{array}{cccccccc} & RT & SP & IP & INF & TERM & RISK & RATE \\ \Sigma_1 = & \multicolumn{7}{c}{\left[\begin{array}{ccccccc} 3315.324 & & & & & & \\ 1554.521 & 1641.364 & & & & & \\ 91.981 & 16.762 & 46.368 & & & & \\ -10.625 & -19.041 & -0.118 & 5.868 & & & \\ 5.126 & 0.089 & -0.144 & -0.126 & 0.177 & & \\ 0.110 & 0.527 & -0.125 & 0.024 & 0.001 & 0.099 & \\ -7.504 & -1.192 & 0.634 & 0.140 & -0.215 & -0.013 & 0.334 \end{array}\right]} \end{array} \qquad (3.6)$$

[17] The scales for all elements in each covariance matrices are adjusted by multiplying by 10^6.

$$
\begin{array}{cc}
& \begin{array}{ccccccc} RT & SP & IP & INF & TERM & RISK & RATE \end{array} \\
\Sigma_2 = & \begin{bmatrix}
1134.401 & & & & & & \\
703.269 & 1937.285 & & & & & \\
-26.413 & -25.027 & 28.351 & & & & \\
-5.650 & -8.893 & 1.218 & 3.677 & & & \\
-0.762 & -2.555 & 0.155 & 0.028 & 0.112 & & \\
-0.007 & -0.006 & -0.050 & -0.026 & 0.005 & 0.011 & \\
-1.744 & -0.083 & 0.188 & 0.041 & -0.073 & -0.015 & 0.130
\end{bmatrix}
\end{array}
\tag{3.7}
$$

The homogeneity between both matrices is investigated using multivariate Box's M statistic (1949), which is a likelihood ratio type test. Under the null hypothesis ($\Sigma_1 = \Sigma_2$), the population covariance matrix Σ is $S = n^{-1}\sum n_i S_i$, and S_i under the alternative, where S_i is the sample covariance matrix, where i = 1 for innovations in the pre-break period and 2 for innovations in the post-break period. The test statistic is given here:

$$M = \gamma \sum (n_i - 1) \log \left| S_{u_i}{}^{-1} S_u \right| \tag{3.8}$$

where, $\gamma = 1 - \dfrac{2k^2 + 3k - 1}{6(k+1)(q-1)} \left(\sum \dfrac{1}{n_i - 1} - \dfrac{1}{n-q} \right)$ and S_{u_i} and S_u are unbiased estimators. $S_u = nS/(n-q)$, and $S_u = n_i S_i /(n_i - q)$ [18]. The Box's M statistic follows a chi-square distribution having the degree of freedom, $k(k+1)(q-1)/2$ (=28) where k (=7) and q

[18] This Box's M is adjusted using S_u and S_{u_i} because, from the likelihood ratio, $-2\ln\lambda = n\ln|S| - \Sigma n_i \ln|S_i| = \Sigma n_i \ln\left|S_i^{-1} S\right|$. if n_i is small, then this ratio gives too much weight to the contribution of S. See Mardia *et al.*, pp. 140.

(=2) are the dimension of the covariance matrix and the number of covariance matrices compared, respectively. n_1 and n_2 are 105 and 289, respectively, that is, the number of observations in each period, where $n = n_1 + n_2$.

Alternatively, Jennrich (1970) provides a homogeneity test of covariances, as well as correlation matrices. The Jennrich test is also a chi-square test with the degree of freedom $k(k-1)/2$ where k is the number of variables. The test statistic for Jenrich is as follows:

$$J = (1/2) \cdot tr(Z^2) \tag{3.9}$$

where, $Z = c^{1/2}\overline{R}^{-1}(R_1 - R_2)$, $c = n_1 n_2 /(n_1 + n_2)$, $\overline{R} \equiv (\bar{r}_{ij}) = \left(n_1 R_1 + n_2 R_2\right)/(n_1 + n_2)$, and $\overline{R}^{-1} = (\bar{r}^{ij})$. $tr(\cdot)$ and $diag(\cdot)$ are trace and column vector using diagonal elements of the matrix. R_i indicates the sample correlation matrix having sample size (n_i), *i=1* (before the break) and *i=2* (after the break).[19]

Empirically, the first test, Box's M test, shows the value of the test statistic to be 164.42, which is greater than the 99% critical value ($\chi^2(k(k+1)(q-1)/2) = \chi^2(28) =$ less than 50). The Jennrich test statistic yields a value of 157.22, which is also greater than the 99% critical value ($\chi^2(k(k-1)/2) = \chi^2(21) \approx 39$). Hence, both tests for

[19] To compare correlation matrices through the Jennrich test, the distribution of test statistics changes to $J = (1/2)tr(Z^2) - diag(Z)' S^{-1} diag(Z)$ but is still an asymptotic chi-square distribution with df =k(k-1)/2. where, $S = (\delta_{ij} + \bar{r}_{ij}\bar{r}^{ij})$ and δ_{ij} is Kronecker delta (i.e. identity matrix). – See Jennrich (1970). For recent applications of Jennrich test, refer Bhar (2001), and Carrieri *et al.* (2003)

covariance homogeneity show that covariance matrices of innovations between pre- and post-break periods are not homogeneous.

3.4.2.2 Impulse Response Functions

Next, the dynamic differences of characteristics between returns on REITs and stocks are identified using the impulse response function analysis (see Fig. 3.3). Here, impulse response functions give information on the direction and significance of dynamic responses for a 9 month horizon following an initial shock of each endogenous variable[20].

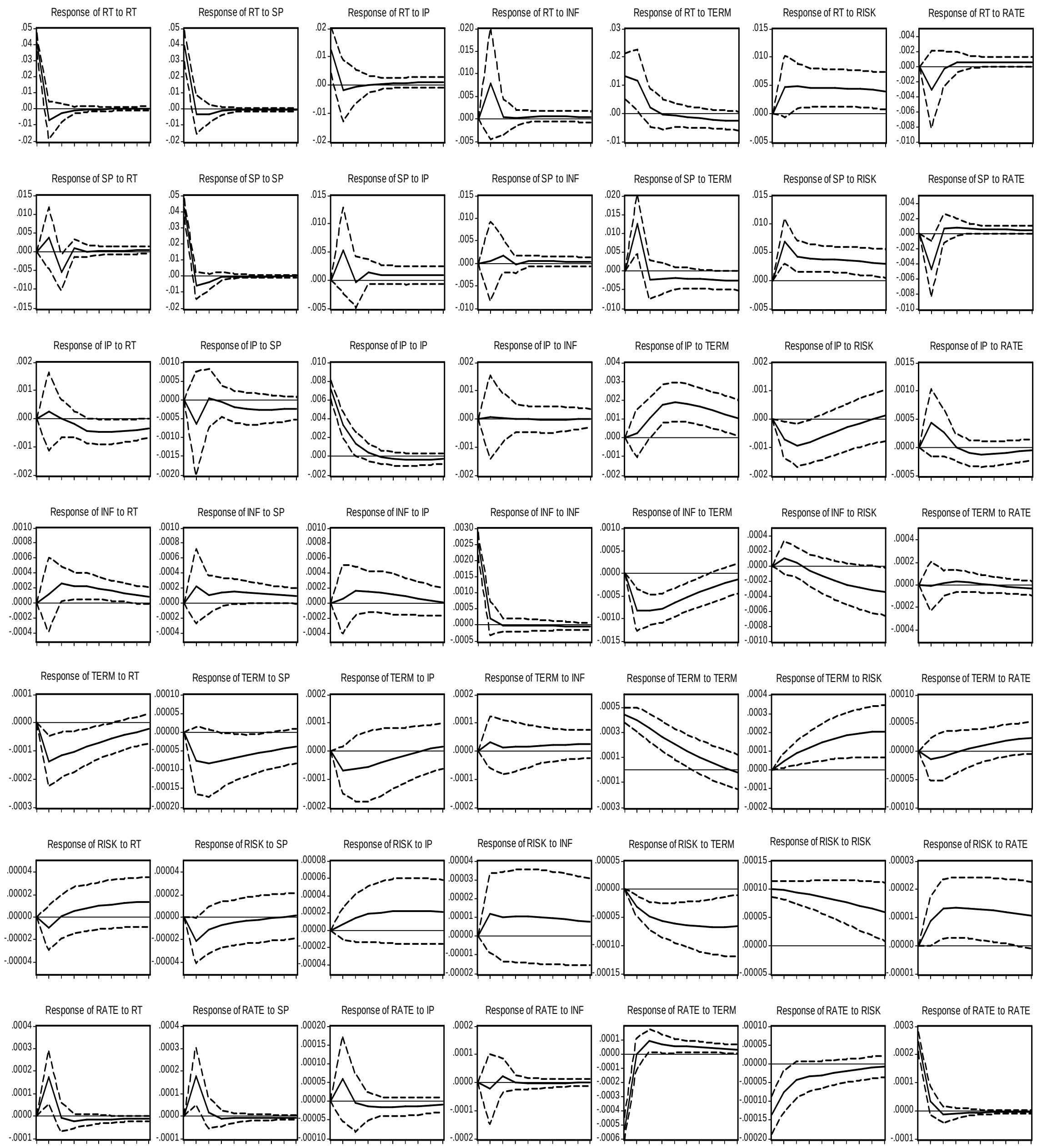
First, a shock to the stock return rate positively affects the return rate for REITs, contemporaneously and dynamically in both the pre- and post-break periods. However, the inverse influences are statistically insignificant for both periods.

Second, a shock in growth rate of industrial production is not an appropriate indicator to decipher the difference between dynamics in returns on REITs and stocks because the both responses of REITs and stocks from the shock have no significant effects in the post-break period. These insignificant responses to a shock in industrial production growth rate arise primarily from market expectation, in that investments on both assets are made by those fundamentals but not temporary shocks.

Third, returns on REITs and stocks show insignificantly negative responses to inflation shock in both periods. Fama and Schwert (1977) investigate an inflation effect on asset returns in a number of assets. They conclude that common stocks seem to

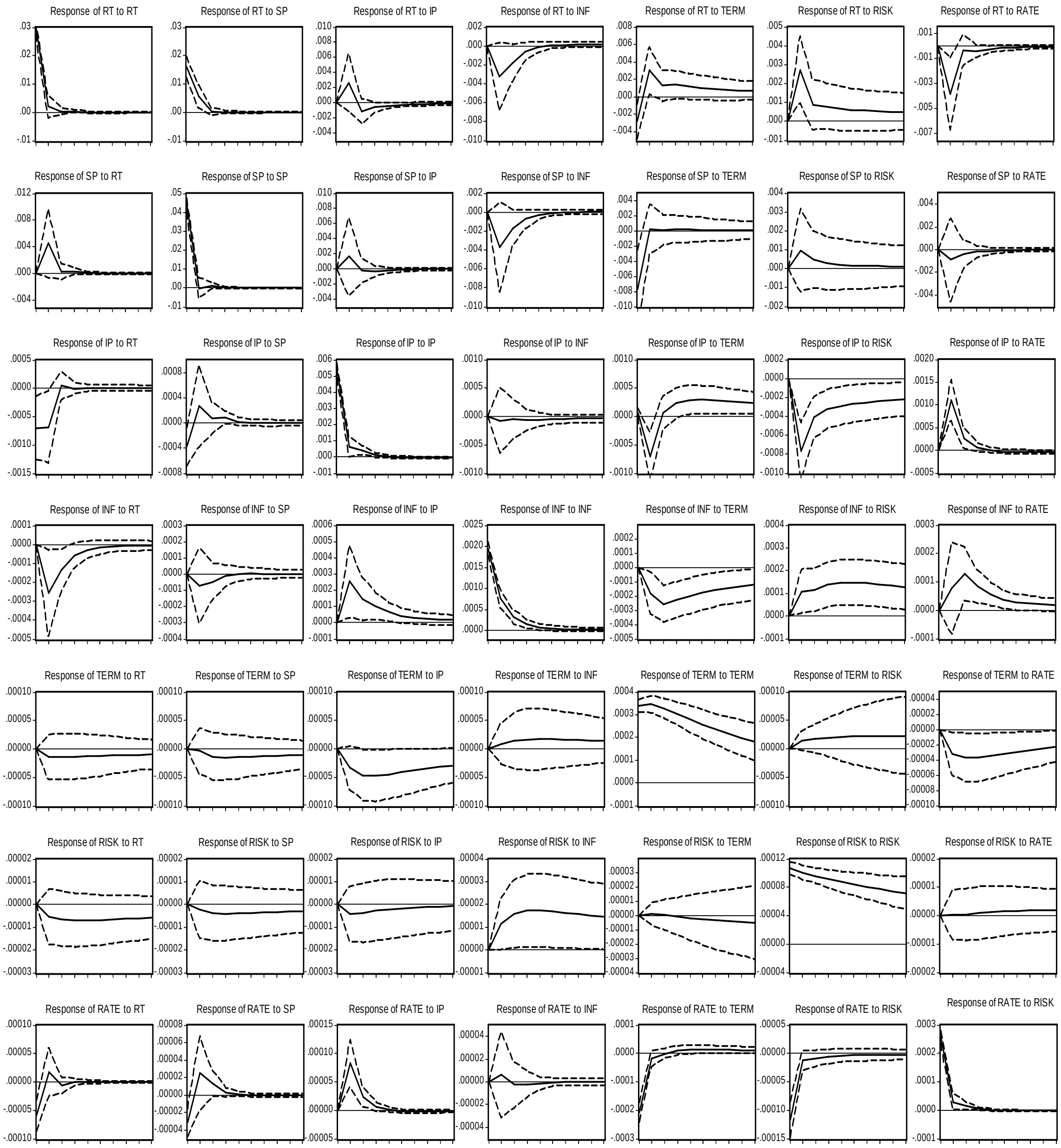
[20] A contemporaneous causal relationship is applied to get orthogonal innovations.

(A) Pre-break period (January 1972-October 1980)



Note: The forecast horizon is measured in months and is given on the horizon. The vertical line shows magnitude of response. The dotted line indicates confidence band, $\pm 2 \cdot S.E.$ The abbreviations are RT (REITs return rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

Fig. 3.3. Impulse response.



(B) Post-break period (November 1980-November 2004)

Fig. 3.3. (*Continued*).

perform poorly as a hedge against both expected and unexpected inflation. Adrangi *et al.* (2004) show negative correlation between a real return of REITs and unexpected inflation. One of the well-known relationships regarding REITs and inflation is that both are negatively dynamically correlated (Lu and So, 2001). Even though the contemporaneous causations found in this chapter do not provide direct contemporaneous causation between the two, dynamic results show a negative relationship because shock in REITs returns helps to reduce inflation rates over the first five months. Even though the negative response of REITs returns to inflation shock is barely insignificant, this dynamic has important implications for market expectations. Once unexpected inflation is realized, market participants would expect the Federal Reserve Bank to increase interest rates; this has reduced incentive to change portfolios to real estate and stocks. However, this inflation factor also seems not to be useful for discriminating dynamics of returns on both assets.

Fourth, dynamic responses in returns on REITs and stocks from a term spread shock are consistent in each period. However, there are big differences in the dynamics between both sub-samples (before and after the break). Before the break, both responses show significantly positive responses to term spread shock. In contrast, they show commonly negative instantaneous responses and recovery dynamics after the break. Generally, a positive change of term spread is known as a signal for future inflation or future economy expansion. Contrary to the effect of the former signal,[21] the latter signal

[21] A poxy hypothesis of Fama (1981) says there is a negative relationship between expected inflation and real activity and a positive relationship between expected inflation and real stock. However those relationships are not clear because unexpected inflation shock is considered as well as nominal stock return.

clearly implies increases in demand of assets. This result supports that the latter signal appears to dominate the negative factor in the former signal. Once a market realizes it is a temporary shock, the preceding dynamic responses show recovery. Here, the contemporaneous negative response of a real estate return to term spread shock after the break is mainly due to the response of stock return to term spread shock rather than direct response because it arises from a contemporaneous front door path TERM→SP→RT. Hence, the positive instantaneous correlation in the pre-break period between real estate and term spread is no longer valid. That is, if stock return is considered as an interim variable to study correlation between a real estate and a term spread, it turns out negative (Brooks *et al.* 1999); otherwise, it can only be positive (Plazzi, 2005). Empirically, partial correlation between real estate return and term spread given stock return ($= Corr(RT, TERM \mid SP)$)[22] is negative, -0.14988, even if the non-partial sample correlation ($= Corr(RT, TERM)$) is positive, 0.1098, between real estate return and term spread.[23] Taking this into account, instantaneous responses of real estate to term spread shock before the break are just positive because DAG shows a directed edge from term spread to real estate returns in the post-break period. Hence, the term spread factor is good for comparing periodical characteristics of both assets between two sample periods, but is not useful for understanding different dynamics of both assets.

Fifth, real estate becomes a more popular tool than common stock assets to manage unexpected default risk shock after the break, because both assets show significantly positive dynamic responses before the break, but only real estate responds significantly

[22] The $Corr(i, j \mid k)$ indicates a partial correlation between *i* and *j* given *k*.
[23] Calculation for partial correlation is shown at Whittaker (1990).

after the break. That is, the results indicate that real estate becomes a relatively useful hedge tool to control default risk increase in a portfolio.

Sixth, the responses of real estate return and stock return to shock in the short run interest rate change (RATE) show an important difference. A shock to interest rate change significantly affects only stock return before the break and only real estate return after the break. In other words, the negative response of real estate return to interest rate shock becomes significant, but the relationship of stock return to interest rate shock looses significance after the break. A possible reason for this stock response arises from the financial industry, which is included in a general stock index and shows the preceding growth since monetary policy change in the late 1970s. In point that Tufte *et al.* (1999) show a positive relationship between general stock and interest rate in financial industry, the negative relationship between stock return and interest rate change becomes vague. Also, REITs have a more economic-based opportunity and become a more important asset through real estate market expansion. Hence, a negative response in real estate return to interest rate shock becomes significant after the break. The well-known inverse relationship between risk free asset and risky assets turns out to be relatively more apparent between real estate and interest rate.

The impulse response functions in the post-break period presented in Fig. 3.3 show four symmetric bilateral relationships with respect to the same sign under significance. Those four relationships are (RATE, RT), (RATE, TERM), (RATE, IP), and (RISK, INF). The first two relationships show negative dynamics and the other two relationships indicate positive dynamic correlations, bilaterally.

3.4.2.3 Other Relationships Among Macroeconomic Variables

Here, the dynamic relationships found among macroeconomic variables with significance (see Fig. 3.3 for the post-break period) can be supported by previous literature. Four important features in macroeconomic variables support existing studies.

First, term spread shock has a temporarily negative effect on real output growth. Then, it changes to a positive effect as time goes by. Estella (2004) explains that term spread takes into account future output growth. However, Crespo-Cuaresma *et al.* (2004) explain that term spread and output can be positively or negatively correlated in a theoretical view.

Second, output growth shock leads to positive future inflation. However, inflation shock has a negative effect on future output, although it is insignificant. This phenomenon can be supported by Taylor (1999), which cites that output positively affects future inflation (Stock and Watson, 1999), but inflation negatively influences future output (Christiano *et al.*, 1998). Also, Fair (2002) shows an inflation shock with the nominal interest rate held constant has a negative effect on real output.

Third, the results show negatively correlated dynamic relationships from a shock in interest rate change to term spread, and from term spread shock to interest rate change. For literature survey, see Ang and Bekaet (2004).

Fourth, default risk shock is a useful tool to predict decreasing output and increasing inflation based on the results. This result is consistent with De Bondt (2002) which provides that corporate bond spread is potentially a useful indicator for future inflation and output growth. However, output growth shock and inflation shock have no significance for dynamic movement of default risk.

3.4.2.4 Forecast Error Variance Decompositions

The forecast error variance decomposition analysis over the preceding twelve months using contemporaneous causal relationships is shown in Table 3.2. This enables us to examine dynamically the relative influence of innovations in each endogenous variable out of the total variation of a variable.

One of the most apparent features in Table 3.2 is that stock and real estate returns are more exogenous in the post-break period relative to in the pre-break period. That is, the share of variation explained by their own innovations increases in the post-break period. For example, the shares of real estate return variation explained by its own innovations are less than 50% before the break and over 70% after the break.

Also, the self explanatory share of stock return variation tends to increase over the break in all 12-month horizons, except for the instantaneous effect. This increased exogeneity in the post-break period is a common phenomenon for all variables. In particular, the following five important pieces of evidences are reported. First, shock in growth rate of industrial production more fully accounts for a variation in interest rate change in the post-break period. That is, the variation in interest rate change that is explained by an IP shock is, for all horizons, less than 1% before the break but over 5% after the break. This is because monetary policy uses the interest rate to control production of economy.

Table 3.2
Forecasting error variance decompositions

(A) Pre-break period (January 1972 – October 1980)

Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
Variance Decomposition of RT:								
0	0.06	47.68	43.18	4.30	0.00	4.84	0.00	0.00
1	0.06	45.37	40.19	4.08	1.62	7.91	0.59	0.24
2	0.06	45.03	39.99	4.04	1.60	7.92	1.19	0.24
12	0.06	42.48	37.76	3.97	1.56	8.67	5.23	0.31
Variance Decomposition of SP5:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.04	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.05	0.65	87.17	1.34	0.01	7.45	2.29	1.10
2	0.05	1.97	85.00	1.30	0.15	7.45	3.04	1.09
12	0.05	1.92	78.55	1.58	0.20	9.25	7.37	1.13
Variance Decomposition of IP:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.01	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.01	0.09	0.64	98.02	0.01	0.09	0.86	0.29
2	0.01	0.09	0.60	95.02	0.01	1.74	2.16	0.38
12	0.01	1.61	0.95	71.07	0.01	22.55	3.46	0.34
Variance Decomposition of INF:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00
1	0.00	0.19	0.74	0.05	89.62	9.25	0.16	0.00
2	0.00	1.01	0.83	0.39	80.72	16.89	0.17	0.00
12	0.00	2.73	1.79	0.99	59.29	27.49	7.63	0.08
Variance Decomposition of TERM:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00
1	0.00	4.92	1.53	1.21	0.24	91.41	0.65	0.05
2	0.00	6.09	2.41	1.64	0.20	87.59	2.02	0.05
12	0.00	5.59	3.44	1.60	0.54	56.49	31.97	0.37
Variance Decomposition of RISK:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
1	0.00	0.42	2.05	0.21	0.68	4.28	92.01	0.35
2	0.00	0.27	1.69	0.74	0.75	9.86	85.96	0.73
12	0.00	1.14	0.53	3.52	0.76	33.35	59.49	1.22
Variance Decomposition of RATE:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	0.00	78.29	5.10	16.61
1	0.00	6.96	7.29	0.79	0.13	65.17	5.56	14.10
2	0.00	6.78	7.14	0.78	0.24	65.48	5.83	13.76
12	0.00	6.75	6.79	1.03	0.24	66.04	6.20	12.96

Table 3.2 (*Continued*)

(B) Post-break period (November 1980 – November 2004)

Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
Variance Decomposition of RT:								
0	0.03	77.49	21.83	0.00	0.00	0.68	0.00	0.00
1	0.04	72.55	22.92	0.56	0.85	1.35	0.60	1.18
2	0.04	72.14	22.79	0.66	1.10	1.46	0.65	1.19
12	0.04	71.44	22.57	0.72	1.13	2.04	0.89	1.21
Variance Decomposition of SP5:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.04	0.00	97.00	0.00	0.00	3.00	0.00	0.00
1	0.05	1.01	95.15	0.13	0.68	2.95	0.05	0.04
2	0.05	1.01	94.99	0.13	0.82	2.94	0.06	0.05
12	0.05	1.02	94.93	0.14	0.85	2.94	0.07	0.05
Variance Decomposition of IP:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.01	1.68	0.47	97.83	0.00	0.01	0.00	0.00
1	0.01	2.95	0.65	89.28	0.02	1.55	1.81	3.75
2	0.01	2.92	0.66	88.65	0.02	1.54	2.30	3.91
12	0.01	2.81	0.66	85.38	0.08	3.28	4.00	3.80
Variance Decomposition of INF:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00
1	0.00	1.44	0.12	1.42	95.94	0.70	0.25	0.13
2	0.00	1.75	0.16	1.78	93.27	2.05	0.51	0.47
12	0.00	1.68	0.15	1.99	85.41	6.24	3.84	0.70
Variance Decomposition of TERM:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00
1	0.00	0.09	0.01	0.47	0.03	98.88	0.08	0.43
2	0.00	0.12	0.06	0.94	0.07	97.98	0.14	0.68
12	0.00	0.19	0.19	1.84	0.28	95.73	0.62	1.15
Variance Decomposition of RISK:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
1	0.00	0.14	0.02	0.09	0.59	0.00	99.16	0.00
2	0.00	0.22	0.06	0.10	1.21	0.00	98.40	0.00
12	0.00	0.48	0.14	0.06	2.93	0.18	96.18	0.03
Variance Decomposition of RATE:								
Period	S.E.	RT	SP	IP	INF	TERM	RISK	RATE
0	0.00	2.74	0.77	0.00	0.00	33.45	10.54	52.50
1	0.00	2.78	1.17	5.00	0.03	31.47	9.96	49.59
2	0.00	2.78	1.29	5.34	0.04	31.23	9.94	49.38
12	0.00	2.75	1.28	5.32	0.04	31.86	9.89	48.85

Note: The abbreviations are RT (REITs return rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

Second, the explanatory share of inflation shock for variation of REITs returns decrease in the post-break period, but for variation of stock return it increases. A variation in real estate return is explained by inflation shock about 1.6% of its variation for all horizons before the break but only 0.85% (short horizon) to 1.13% (longer horizon) after the break.

Third, a shock in interest rate change tends to make other variables more volatile in the post-break period. For variations of real estate return, industrial production, inflation, and term spread, a shock in interest rate takes account for 1.18-1.21%, 3.75-3.8%, 0.13-0.70%, and 0.43-1.15%, respectively, which demonstrates an increase for all horizon compared to those in pre-break period. This is because the FRB is targeting inflation rates using interest rates.

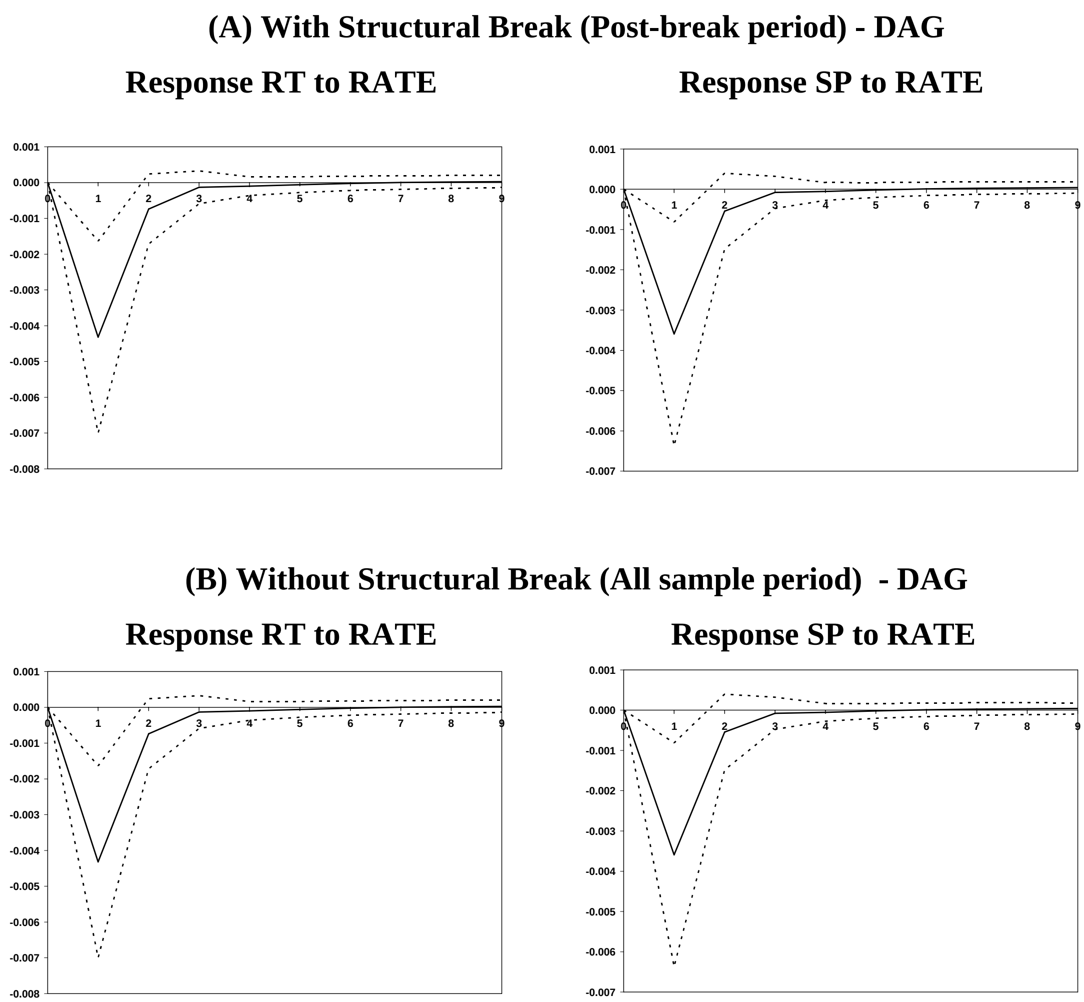
Fourth, the influence of real estate sector on other variables increases in the post-break period. As expansion of REITs market, REITs becomes more effect on other variables. After the break, real estate return shock has an increased effect on variations in a stock return, industrial production growth, inflation, and interest rate change. Especially, the variation share of interest rate change increases at the zero-month horizon, from 0% to 2.74%. The variation shares of stock return and inflation at the one-month horizon are 1.01% and 1.44% after the break compared to 0.65% and 0.19%, before the break. Clearly, the effect of real estate shock on industrial production growth increases for all horizons after the break, compared to before the break. However, after the break, stock return shock loses influence towards over all variables except industrial production movement. Particularly, innovation in stock return shows relatively high and persistent effect (about 22% in any horizon) on real estate returns in the post-break period.

Fifth, the change in monetary policy in the late 1970s causes short-term interest rates to have strong dynamic relationships with industrial production growth (IP) and default risk (RISK). That is, before the break, IP and RISK shocks explain variation in interest rate change by 0.79% and 5.56% at the one-month horizon, and by 1.03% and 6.20% at the 12-months horizon. However, after the break, their explanation powers increase to 5.0% and 9.96% at the one-month horizon, and to 5.32% and 9.89% at the 12-months horizon.

3.4.3 One-period Analysis

In this section, dynamics without considering structural break is investigated using impulse response analysis, in order to provide the reasonable evidence why it is necessary to consider structural break in this model. The focus is on the returns to REITs and stock. If the model is estimated using the post-break period rather than all sample period, it implies that structural break is considered. Otherwise, it indicates that estimation ignores the existence of any structural break.

Impulse response functions of returns on REITs and stocks to the changes in interest rate shock with considering structural break (two-periods analysis) and without considering structural break (one-period analysis) are compared (see Fig. 3.4). For comparison, a post-break period is used for one-period analysis and an entire sample period is used for two-period analysis. Fig. 3.5 compares responses in the case of default risk shock.

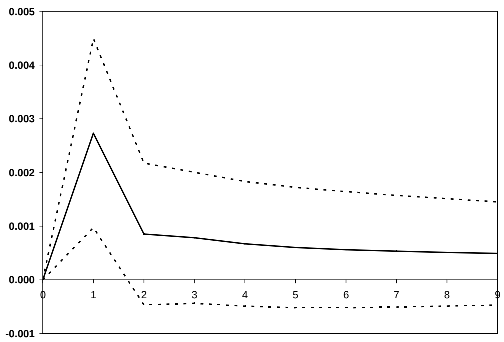


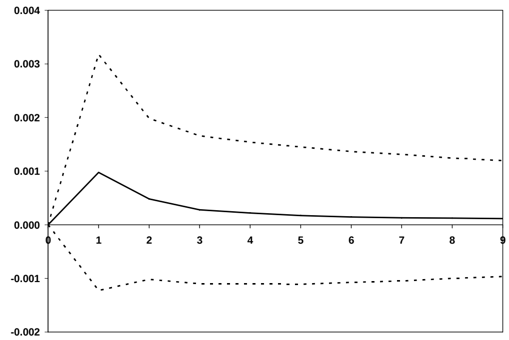
Note: The forecast horizon is measured in months and is given on the horizon. The vertical line shows magnitude of response. The dotted line indicates confidence band, $\pm 2 \cdot S.E.$ The abbreviations are RT (REITs return rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

Fig. 3.4. Comparison of impulse responses – interest rate shock.

(A) With Structural Break (Post-break period) – DAG

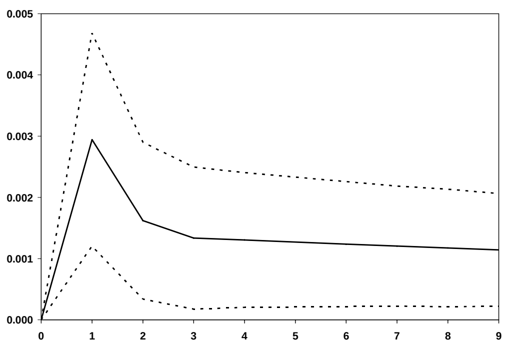
Response RT to RISK **Response SP to RISK**

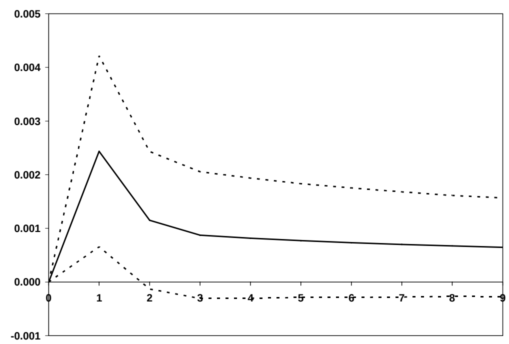




(B) Without Structural Break (All sample period) - DAG

Response RT to RISK **Response SP to RISK**





Note: The forecast horizon is measured in months and is given on the horizon. The vertical line shows magnitude of response. The dotted line indicates confidence band, $\pm 2 \cdot S.E.$ The abbreviations are RT (REITs return rates), SP (stock return rates), IP (industrial production growth rates), INF (inflation rates), TERM (term spread), RISK (default risk), and RATE (short-term interest rate changes).

Fig. 3.5.Comparison of impulse responses – default risk shock

The impulse response graphs which consider structural break are identical to those in Fig. 3.3 (B). However, in case no to consider structural break, impulse response graphs using all data sample period are re-estimated. In this case, DAG analysis is also imposed on dynamic analysis.[24]

Comparison to both dynamics—those considering breaks and those that don't—provides the reason why it is important for us to consider structural break. As Fig. 3.4 and 3.5 show that, if existence of structural break is ignored, the responses of stock and REITs returns to shock in interest rate changes are all significantly negative. Also, shocks to default risk have significantly positive effects on both asset returns. Compared with those, when structural break is considered for dynamic analysis, REITs rates respond to interest rate shock significantly, but stock rates shows insignificant responses to the shock. In this case, REITs only respond significantly to the default risk shock but insignificant to SP. Thus, the empirical model which considers the structural break is more useful to discriminate different recent behaviors between stock and REITs.

3.5 Conclusions

This study builds an econometric model, which can provide useful explanation for recent movements in returns on REITs and stocks in response to decreasing interest rates. To determine clear discrimination between movements of REITs and stock returns, a VAR using other macroeconomic variables (inflation rate, growth rate of industrial production, default risk, and term spread) is used.

[24] The contemporaneous causation for orthogonalization for DAG is shown at Figure 1. C.

Also, a structural break with unknown break point, which some previous studies are interested in, is investigated. It enables us to find consistent sub-sample periods having stable parameter values in a given framework when the break point is unknown. Using these tests, a single break point (T^*) is detected in October 1980. This unique single break point is strongly supported in three endogenous variables system—real estate returns, stock returns, and interest rate changes. This change is likely due to the monetary policy changes established by Paul Volker, Chair of the Federal Reserve Bank, as they affected the economy. The structural break point found in this study is different from previous studies; Chui (2003), Ewing and Payne (2005), and Paynes (2003) just assumed the break points was at December 1989, December 1979, and September 1982, respectively, without a test. Also Okunev *et al.* (2000) found it at July 1989, but they did not consider a comprehensive test of stability for parameters. Moreover, there is no study to test possible existence of multiple structural breaks.

Based on DAG analysis, returns on REITs have a more causal ability after the break compared to before the break. The results regarding contemporaneous causation show that real estate has changed from a sink to a parent in terms of innovation discovery[25] for short-term interest rates and industrial production. This suggests that real estate investment has a more exogenous role after the break. The Bernanke decomposition supports that above contemporaneous findings (See Table 3.2.).

The impulse response analysis provides an important implication for recent different movement in returns of REITs and stock. When only a post-break period is considered in

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[25] See Pearl (2000).

the dynamic analysis, the responses of REITs returns to default risk and interest rate change risks are significantly positive and negative, respectively. At the same time, the responses of stock return to those shocks are not significant in the post-break period. REITs are very interest rate sensitive: while S&P 500 is an aggregate over many companies. Some of which are not as responsive to interest rates or are at different points in the business cycle, not particularly sensitive to current interest rates. This analysis shows significantly positive responses of real estate returns due to an initial shock in default risk but insignificant responses due to innovation in stock returns. During the first three years in 2000s, default risks increased and interest rate changes decreased.

It is important to consider structural change in modeling REITs. When an all sample period is used in the model (i.e. removing the consideration of a structural break), distinct differences in dynamics between returns on both assets are not found.

In this chapter, robust results on causality and dynamics for returns on risk assets have been investigated under a test-based structural break. This inter-temporal comparison between pre- and post-break enables us to identify and verify the role of REITs in a real economy in aspects of dynamics and causalities.

CHAPTER IV

STRUCTURAL CHANGE IN STOCK PRICE VOLATILITY IN ASIAN FINANCIAL MARKETS

4.1 Introduction

Generally, Asian financial markets are known to respond predictably to economic events. In particular, important economic events[26] have had comprehensive and indirect effects on the Asian financial markets and the world economy, including risk premiums in debt market (Allen and Gale (1999, 2000), Bello (1997), Emmons *et al.* 2000, Johnson (1998), Koo (2003), and IMF report (1998)). Ayuso and Blanco (2001) demonstrate that during the nineties, there was a genuine increase in the degree of integration among the world stock markets. In this sense, many studies have mentioned the potential structural change with respect to financial market risk in Asian financial markets (Allen and Gale (1999, 2000), Andreou and Ghysels (2002), Chaudhuri *et al.* (2004), and Emmons *et al.* (2000)). However, there has not been a comprehensive and in-depth study that addresses and focuses on the potential (multiple) change(s) and on properties of the change(s) with respect to volatility[27] in Asian financial markets.

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[26] Japan bubble burst (early 1990s), Gulf war (1991), the collapse of the USSR (1991), the Tequila effect in Mexico (1994), the Asian crisis (1997), the world trade center disaster (2001), and Severe Acute Respiratory Syndrome (SARS) (2003)

[27] Volatility is usually referred to as the (annualized) standard deviation of the price return rate. In this study, we refer volatility as conditional standard deviation without annualizing, for convenience.

It is important for investors, analysts, and policy makers to predict volatility since they should prepare for possible unexpected price change in advance. Conceptually, volatility implies the degree of uncertainty (or risk)[28] in price change, because the value of the volatility will be relatively high (low) when the price of stock experiences huge (small) swings in a short period. Risk is defined as the possibility of an unpleasant event. In many investment cases, volatility can be used to calculate lower bounds for the probabilities of these events. To analyze behavior of volatility, price movement is divided by the expected and unexpected portion of the change in value. Since the unexpected change is related to risk and volatility, volatility is useful information in making investment decisions; see Hopper (1996). However, if there is a structural change in the volatility pattern of an economic variable using a given sample period, prediction of volatility from the model without considering the structural change may no longer be consistent and reasonable.

Studies have used alternative methods to test for possible structural breaks in Asian financial markets. Andreou and Ghysels (2002) use two tests to look for structural change in volatility for Asian financial markets: one is a CUSUM type test[29] used by Kokoszka and Leipus (2000) and another is a least squares type test used by Lavielle and

[28] See Tsay (2002, pp.80)

[29] Hsu *et al*. (1974) begin to use this CUSUM test for structural change in volatility. They construct a test based on the alternative probability model of stock return data rather than using a Paretian distribution. Through evidence of non-normality − fat-tail − of the stock return series, they introduce variance as a non-stationary example. Recently, Inclan and Tiao (1994) detected variance changes based on an Iterated Cumulative Sum of Squares (ICSS) algorithm. However, Chihwa and Ross (1995) criticized the standard CUSUM test in Inclan and Tiao (1994) because its performance is quite disappointing. They propose a modified Cumulative Sum of Squares (a modified CUSUM) test for handling serially correlated data. Additionally, Kim, Cho, and Lee (2000) point out that Inclan *et al.* (1994) CUSUM test in GARCH performs appropriately under limited conditions. Kokoszka and Leipus (1999, 2000) develop a theoretical CUMSUM test of variance change in the (G)ARCH model.

Moulines (2000). Chaudhuri *et al.* (2004) also provide evidence of regime switching with respect to the volatility patterns due to the Asian financial crisis in four Asian financial markets: Indonesia, Korea, Malaysia, and Thailand. They use a regime switching method to test for a structural break, but they do not consider a detection of change point and the Asian financial hub (Hong Kong and Singapore). However, Hill (2004) suggests that the Sup LM sup test out-performs the other traditional test methods. Kim *et al.* (2000) point out that the CUSUM test in GARCH used by Inclan *et al.* (1994) performs appropriately under limited conditions. Smith (2004) provides that the CUSUM tests tend to over reject even in quite large samples when returns have fat tails.

As an alternative method effective for testing structural change in volatility, Chu (1995) reports a good power of test by employing a Supremum (Sup) F and Sup LM tests, which are inspired by Andrews (1993). Along this line, Smith (2004) finds that Sup LM, rather than the CUSUM test improves the power of tests that use artificial data. Also, the empirical study by Smith (2004) detects a structural change in volatility of the S&P 500 in 1989. This type of methodology enables the exposure of multiple structural changes in the case of an unknown break point while achieving stronger test power rather than that achieved by the CUSUM test. No other studies have addressed the Asian financial markets comprehensively with respect to (multiple) structural change(s) in volatility using the Sup LM test. Further, no one has addressed the properties of coefficient changes in GARCH representations in the financial market literature. Also no one has studied about change pattern in volatility in case of existence of (multiple) structural change(s) in volatility.

The objective of chapter IV is to test for evidence of structural change in volatility of Asian financial markets from 1990 to 2005 using the Sup LM test rather than other test methods used previously, and to correct for structural change if present. The possibility of multiple structural changes existing will also be investigated. Each of the structural change in volatility points will be determined and incorporated into the study. Moreover, if structural change(s) in volatility exist in any of the financial markets, the main feature of the volatility structure change will be identified.

4.2 Empirical Modeling

Basically, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) which has been developed after the introduction of the Autoregressive Conditional Heteroskedasticity Model (ARCH) by Engel (1982) can account for the fat-tail[30] phenomenon from the volatility clustering behavior[31] (a type of heteroskedasticity). Using the GARCH model[32] which was developed after the introduction of the Autoregressive Conditional Heteroskedasticity Model (ARCH) by Engel (1982), evidence of structural change in volatility in Asian financial markets is tested using the Sup LM test (Andrews (1993), Chu (1995), and Simth (2006)). In the case of the

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[30] The normal distributions have a kurtosis of 3 (irrespective of their mean or standard deviation). If a distribution's kurtosis is greater than 3, it is said to be leptokurtic. If its kurtosis is less than 3, it is said to be platykurtic. Leptokurtosis is associated with distributions that are simultaneously "peaked" and have "fat tails."

[31] Asset returns are approximately uncorrelated but not independent through time as large (small) price changes tend to follow large (small) price changes. This temporal concentration of volatility is commonly referred to as 'volatility clustering' – Karmakar (2003)

[32] Books (2002) argues that if the errors are heteroskedastic, but assumed homoskedastic, one implication would be that standard error estimates could be wrong.

existence of structural change, change points will be detected using ideas from Bai (1994, 1997), Yao (1987), and Liu *et al.* (1997).

Books (2002) argues that if the errors are heteroskedastic, but assumed homoskedastic, this would imply that standard error estimates could be wrong. In this case, it is reasonable to construct an econometric model that assumes heteroskedasticity, of which variance evolves over time. Hence, it is important to set up time series model including volatility to increases efficiency[33].

Bollerslev (1986) suggests that the *Generalized* Autoregressive Conditional Heteroskedasticity (GARCH) reduces the exploding parameter numbers in the ARCH model (Engel, 1982) and so maintains the parsimonious rule in the econometric model. The GARCH model measures the persistence, as well as the sensitivity of volatility. The intuition of the heteroskedasticity model is that although successive innovations are uncorrelated with a mean of zero, they are not independent over time with respect to conditional volatility series (Dengiannakis and Xekalaki, 2005). The heteroskedasticity can be considered as time-varying variance, i.e. volatility clustering or persistence. Also autoregressive conditional indicates that a feedback mechanism exists using the immediate past observations.

The following GARCH(1,1) model,[34] adds a dummy variable (D_t) from original version specification to test existence of structural change in the volatility equation:

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[33] Tsay(2002, pp.79) provides that modeling volatility of a time series can improve the efficiency in parameter estimation and the accuracy in interval forecast.
[34] It can be extended to GARCH(p,q).

$$y_t = \phi_0 + \sum_{i=1}^{I} \phi_{1i} y_{t-i} + \sum_{j=1}^{J} \phi_{2j} z_{t-j} + u_t \quad (4.1)$$

$$\sigma_t^{\ 2} = \varpi + \alpha\ u_{t-1}^{\ 2} + \beta\ \sigma_{t-1}^{\ 2} + \delta_1 D_t + \delta_2 u_{t-1}^{\ 2} D_t + \delta_3 \sigma_{t-1}^{\ 2} D_t, \quad (4.2)$$

where D_t is 1 if $t > T^*$ or 0 otherwise. And T^* is the possible break point in volatility. Here, y_t and z_t are the log difference form of each stock index and foreign exchange rate. For observed time series y_t and z_t, the series $u_t\ (= \sigma_t e_t,\ \ e_t \sim \text{iid}(0,1))$ and $\sigma_t^{\ 2}$ are the innovation and conditional variance, respectively. Equation (4.1) is a *mean equation,* estimates the coefficients $-\phi_0$, ϕ_{1i}, and ϕ_{2j}. Equation (4.2) is a *conditional variance equation,* estimates the coefficients $-\varpi$, α, β, δ_1, δ_2, and δ_3. The optimal lag lengths for *I* and *J* in equation (4.1) are chosen by Schwarz loss criterion. ϖ, α, and β are defined, respectively, as a constant coefficient of volatility, an ARCH impact coefficient implying short-run adjustment from immediate past shock, and a GARCH persistence coefficient implying a relatively long-run pattern of volatility, respectively.

For the estimation method in GARCH, a quasi-maximum likelihood (QML)[35] estimator is used by imposing on the Gaussian log likelihood function in each GARCH(1,1) model. Bauwens *et al.* (2006) summarizes that this Gaussian log likelihood enables us to calculate the quasi-maximum likelihood (QML) estimator, which is consistent for the parameters even if the true density is different from the

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[35] Hardle *et al.* (2002) summaries that maximizing the Gaussian log-likelihood function becomes the quasi-maximum likelihood (QML) if the true distribution of innovations is non-Gaussian - (see the section 10.1.2.). After White (1982) initiates the QML, a number of researches have proved the validity of QML under various conditions - Weiss(1986), Bollerslev *et al.* (1992), Lee *et al.*(1994), Lumsdaine (1996), and Comte *et al.* (2003).

Gaussian distribution. Of course, the Maximum Likelihood (ML) estimator, which requires the true density, is more efficient than the QML estimator. There have been many attempts assuming non-Gaussian distribution of innovations rather than QML using Gaussian distribution. Usually, the student t-distribution assumption is proposed rather than the multivariate Gaussian distribution (Harvey *et al.*, 1992). However, Bollerslev and Wooldridge (1992) suggest and prove that under some certain conditions the parameter estimation through QML is still consistent even if the innovations are non-normally distributed,[36] see Jeantheau (1998), Engle *et al.* (2001a), and Bauwens *et al.* (2005). Also if we use the ML assuming the non-normal distribution, it may bring about serious failure because it can not even guarantee at least consistency if the assumed distribution is incorrect. Therefore, the QML estimation method is used the following the GARCH estimation.

When the conditional variance (σ_t^2) is expected by past innovations and past conditional variances, the focus is whether the parameters, $\delta\,(=(\delta_1, \delta_2, \delta_3))$ are zero or not. Because the null hypothesis ($H_0 : \delta = 0$) assumes there is no structural change and the alternative hypothesis ($H_1 : \delta \neq 0$) implies existence of structural change, this Sup LM test is parameter stability test in the conditional variance equation. By definition, the possible break point (T^*) is considered as a portion (τ) of the total observations (*n*).[37]

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[36] See Theorem 2.1 at pp. 148, and Conditions A.1 at pp 167 in Bollerslev and Wooldridge (1992)

[37] Hence, when dummy variable (D_t) is not considered, the other expression of alternative hypothesis is expressed by:

Given the auxiliary condition of normality, the likelihood function can be defined as follows:

$$L_n(\phi,\theta,\delta,\tau)=\sum_{t=1}^{[n\tau]} l_t(\phi,\theta,\delta)+\sum_{t=[n\tau]+1}^{n} l_t(\phi,\theta,\delta) \tag{4.3}$$

where $\phi=(\phi_0,\phi_{1i},\phi_{2j})$ and $l_t(\phi,\theta,\delta)=-\frac{1}{2}\ln\sigma_t{}^2(\phi,\theta,\delta)-\frac{1}{2}\frac{u_t{}^2(\phi,\theta,\delta)}{\sigma_t{}^2(\phi,\theta,\delta)}$

For the LM test, the score, $g_n(\theta,\tau)$, can be defined using the likelihood function of GARCH:

$$g_n(\phi,\theta,\delta)=\frac{1}{\sqrt{n}}\sum_{t=1}^{[n\tau]}\frac{\partial l_t(\phi,\theta,\delta)}{\partial\delta} \tag{4.4}$$

where $\frac{\partial l_t(\phi,\theta,\delta)}{\partial\delta}=\left[\frac{\partial l_t(\phi,\theta,\delta)}{\partial\delta_1},\frac{\partial l_t(\phi,\theta,\delta)}{\partial\delta_2},\frac{\partial l_t(\phi,\theta,\delta)}{\partial\delta_2}\right]'$

Under the null hypothesis ($H_0:\delta=0$), the restriction renders the likelihood function (4.3) be the same as the likelihood function without structural change. The standard method of estimating the GARCH model can be applied. We denote $\left(\tilde{\phi},\tilde{\delta}\right)$ as the

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$$\begin{aligned} H_{1T}(\pi):\theta_\tau &= \theta_1 \quad for\, t=1,\ldots,n\tau \\ &= \theta_2 \quad for\, t=n\tau+1,\ldots,n \end{aligned}$$

$where,\ \theta_1\neq\theta_2,\ \theta=(\omega,\alpha,\beta)$

estimator[38] of the GARCH model without structural change. Thus, the score function, $g_n(\theta,\tau)$, reduces to the following:

$$\lambda_n(\tau)=\frac{1}{\sqrt{n}}\sum_{t=1}^{[n\tau]}\frac{\partial l_t\left(\tilde{\phi},\tilde{\delta}\right)}{\partial\delta}$$

The information matrix can be defined as follows:[39]

$$Q_n(\tau)=\frac{1}{n}\sum_{t=1}^{[n\tau]}\frac{\partial l_t}{\partial\theta}\frac{\partial l_t}{\partial\theta'}$$

$$=\frac{1}{n}\begin{bmatrix}\sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\omega}\frac{\partial\sigma_t^2}{\partial\omega}, & \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\omega}\frac{\partial\sigma_t^2}{\partial\alpha}, & \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\omega}\frac{\partial\sigma_t^2}{\partial\beta}\\ \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\alpha}\frac{\partial\sigma_t^2}{\partial\omega}, & \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\alpha}\frac{\partial\sigma_t^2}{\partial\alpha}, & \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\alpha}\frac{\partial\sigma_t^2}{\partial\beta}\\ \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\beta}\frac{\partial\sigma_t^2}{\partial\omega}, & \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\beta}\frac{\partial\sigma_t^2}{\partial\alpha}, & \sum_{t=1}^{[n\tau]}\frac{1}{\sigma_t^4}\frac{\partial\sigma_t^2}{\partial\beta}\frac{\partial\sigma_t^2}{\partial\beta}\end{bmatrix}$$

The LM statistic for the null hypothesis ($H_0:\delta=0$) is given by

$$LM_n(\tau)=\lambda_n{}'(\tau)\cdot V_n(\tau)^{-1}\cdot\lambda_n(\tau) \qquad (4.5)$$

where $V_n(\tau)=V\hat{a}r(\lambda_n(\tau))=(\hat{\kappa}-1)\cdot\tau\cdot Q_n(\tau)$ and $\hat{\kappa}=\frac{1}{n}\sum_{t=1}^{n}\frac{u_t^4(\tilde{\phi},\tilde{\theta})}{\sigma_t^4(\tilde{\phi},\tilde{\theta})}$

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[38] $\hat{\theta}$ and $\tilde{\theta}$ are obtained from $l_t(\phi,\theta,\delta)$ and $l_t(\phi,\theta,\delta=0)$, respectively.

[39] Taylor expansion is applied to solve information matrix.

Then, $\lambda_n(\tau)$ weakly converges to the following form of Brownian bridge:

$$\lambda_n(\tau) \Rightarrow W(\tau) - \tau \cdot W(1)$$
$$\left(= (\kappa - 1)^{1/2} Q^{1/2} [B(\tau) - \tau \cdot B(1)]\right)$$

where κ, $W(\cdot)$ and $B(\cdot)$ are kurtosis, Wiener process and standard Brownian motion, respectively. It is due to the following three asymptotic results,

(1) $Q_n(\tau) \xrightarrow{p} \tau \cdot Q$ where, $Q = E\left[\frac{\partial l_t}{\partial \theta} \frac{\partial l_t}{\partial \theta'}\right]$

(2) $V_n(\tau) = V\hat{a}r(\lambda_n(\tau)) = (\hat{\kappa} - 1) \cdot Q_n(\tau) \xrightarrow{p} V(\tau) = (\kappa - 1) \cdot \tau \cdot Q$

(3) $W(\tau) = B(\tau \cdot (\kappa - 1) \cdot Q)$

The Lagrangian Multiplier (LM) statistic has the limiting distribution as follows:

$$\begin{aligned} LM_n(\tau) &= \lambda_n'(\tau) \cdot V_n(\tau)^{-1} \cdot \lambda_n(\tau) \\ &\Rightarrow \lambda'(\tau) \cdot V(\tau)^{-1} \cdot \lambda(\tau) \end{aligned} \tag{4.6}$$

where, $\lambda(\tau) = (\kappa - 1)^{1/2} Q^{1/2} [B(\tau) - \tau \cdot B(1)]$ and $V(\tau) = (\kappa - 1) \cdot \tau \cdot Q$

In this study, the Supremum LM (Sup LM) is applied to test structural change in volatility with unknown point in the portion $[\underline{\tau}, \overline{\tau}(=1-\underline{\tau})]$ with $\underline{\tau}$ =0.15, out of the total sample size; see Andrews (1993).

$$Sup\ LM = \underset{\tau \in [\underline{\tau}, \overline{\tau}]}{MAX} \quad LM_n(\tau) \tag{4.7}$$

Andrews (1993) and Andrews & Ploberger (1994) show that the testing problem is nonstandard because every possible break point should be considered as a nuisance parameter in the case of an unknown break point. Hence, instability of coefficients in the conditional variance equation is tested to find significant evidence of structural change in the volatility structure. Andrews (1993) provides critical values in case of $p=3$ for 10%, 5% and 1% significance levels.

For change point ($T^* = \tau^* \times T$) detection, the value of log likelihood obtained from a joint estimation of equations (4.1) and (4.2) is applied. The idea is taken from minimizing the Sum of Squares Error (SSE) in Bai (1994, 1997), and using Schwarz loss in Yao (1987) and Liu *et al.* (1997). A maximizing likelihood value in the estimation of GARCH does not imply minimizing SSE because GARCH is not a homoskedastic model. In this case, point detection for structural change is a more reasonable tool to find the optimal point to maximize the log likelihood rather than minimizing SSE. Because the estimation of GARCH is a maximizing likelihood function, rather than minimizing SSE, detection using maximization of likelihood is more reasonable than minimizing SSE or Schwarz values. If the null hypothesis in the Sup LM test can be rejected, it supports the existence of a structural change in volatility. In this case, we will find a change point having a maximum likelihood value in a sample portion, $[\underline{\tau}, \bar{\tau}]$, using GARCH – equations (4.1) and (4.2). Hence, the change point is expressed by

$$T^* = \underset{\tau \in [\underline{\tau}, \bar{\tau}]}{\arg\max} \left(\max_{\phi,\theta,\delta} L_n(\phi, \theta, \tau, \delta) \right) \tag{4.8}$$

After the first structural change point is identified and detected, the existence of multiple breaks through repeatedly applying the above procedures–Sup LM test and then detection of the change point–over all sub-sample groups is investigated.

4.3 Data

Six stock indices are used: the Hong Kong Hangseng index, the Japan Nikkei 500 index, the Korea KOSPI, the Singapore Straits Times, the Thailand Bangkok SET index, and the U.S. S&P 500 index. The reason to include U.S. financial market is because Bessler *et al.* (2003) reported that U.S. stock market is dominant to Asian financial markets. Also, for each Asian market, a foreign exchange rate—each currency against the United States dollar—is used as an explanatory variable for stock price movements. Data are daily over the time period 1/1/1990 to 12/31/2005.[40] All stock indices and exchange rates are transformed to logarithms without loss of generality. Based on the

[40] In this chapter, the date is notated by a form of mm/dd/yyyy.

unit root test, all stock indices and foreign exchange rates are instationary, but they become stationary after taking the first difference of logarithm, i.e. *I(1)*.

4.4 Empirical Results

Using all sample period (1/1/1990-12/31/2005), GARCH(1,1) results in the six financial markets, five Asian countries and the U.S., satisfy the condition for weak stationary ($\alpha + \beta < 1$), see Table 4.1.

Table 4.1
Structural change test and point detection

	Break point (mm/dd/yyyy)	Sup LM Test statistics	Test period (mm/dd/yyyy)
Hong Kong	11/2/1993	15.4292**	1/1/1990-12/31/2005
	7/31/1996	12.1665*	11/3/1993-12/31/2005
	12/30/1997	19.3983***	8/1/1996-12/31/2005
Japan	10/6/1992	21.5729***	1/1/1990-12/31/2005
Korea	2/16/1994	13.8127*	1/1/1990-6/28/1996
	6/28/1996	20.4824***	1/1/1990-12/31/2005
Singapore	3/20/1991	12.5996*	1/1/1990-8/7/1997
	8/7/1997	15.2850**	1/1/1990-12/31/2005
	1/29/2004	15.1068**	8/11/1997-12/31/2005
Thailand	-	11.03174	1/1/1990-12/31/2005
United States	-	7.3533	1/1/1990-12/31/2005

Note: *, **, and *** indicate that null hypothesis is rejected in 10% 5%, and 1% significant level, respectively.

Basically, volatility—conditional standard deviation—is obtained from the estimation of GARCH(1,1) with an autoregressive type mean equation.[41] Because the complete sample period is used, it is assumed that there is no structural change in volatility. However, if there is any structural change in volatility, the results provide inconsistent estimators and are the outcome of spurious estimation.

Based on the Sup LM test, all Asian stock markets except Thailand market have structural changes in volatility; see Table 4.1 for Sup LM test statistics, and Table 4.2 for sequence of LM test statistic. By the Sup LM test, four markets (Hong Kong, Japan, Korea, and Singapore) experience structural changes in volatility, but not in the Thailand and the U.S. markets. After detecting effective change point(s), the GARCH model is estimated again over the sub-sample periods divided by the structural change point(s) found and then conditional standard deviations, i.e. volatility, are shown in Fig. 4.1.[42]

From all structural change points shown in Table 4.1, the entire period can be segmented roughly into three phases of sub-samples. The first phase includes the Gulf War (1990-1991), Japan's economic recession from 1992 (Suzuki, 1997), corresponding policy changes. The second phase includes the period showing chaos in financial markets due to the Asian crisis (in the mid-1990s). The last sample group (the first half of 2000s) represents the recovery period for the Asian financial markets. Each sequence for LM test statistics is reported in Fig. 4.2.

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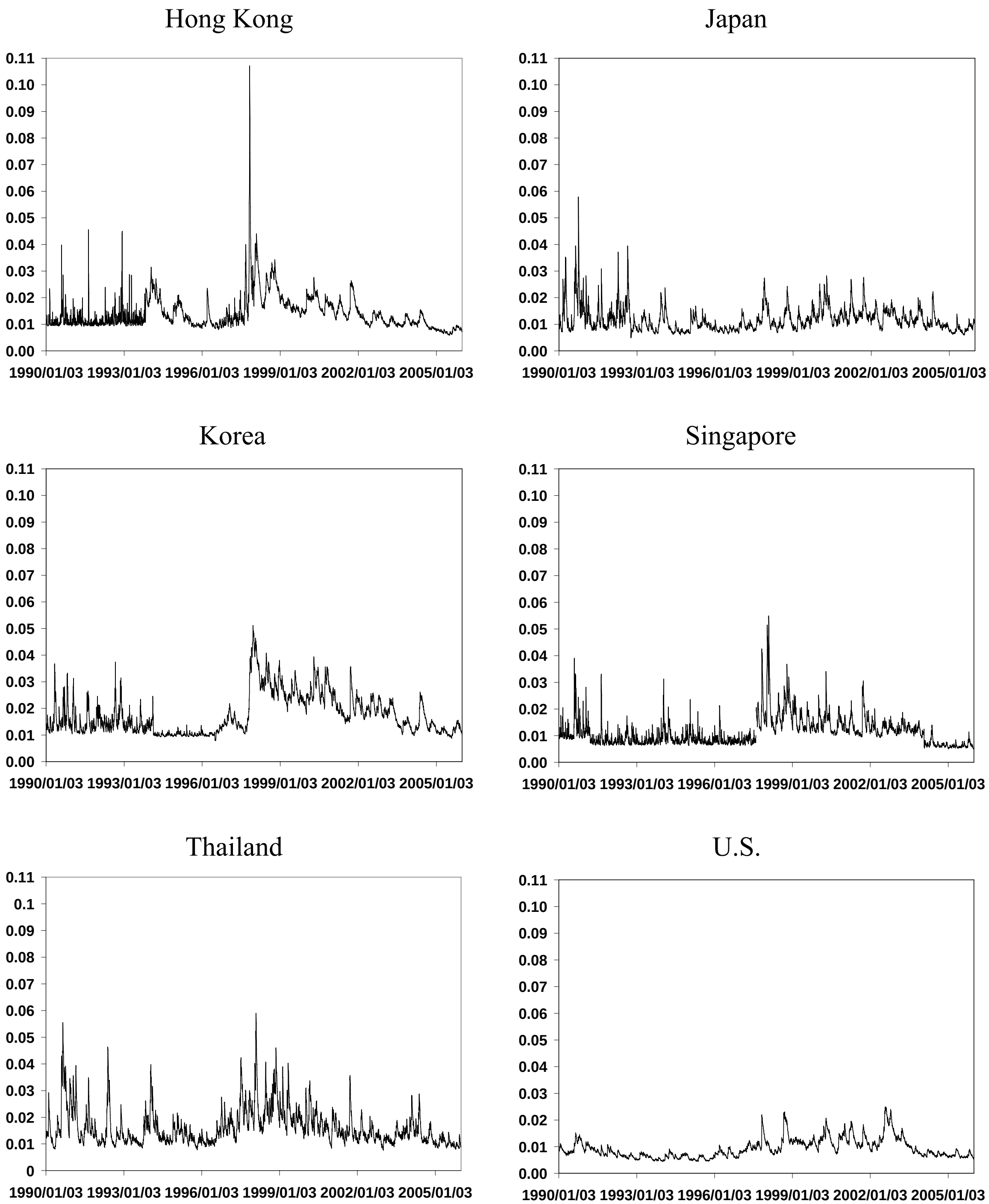
[41] By Schwarz criterion, An optimal lag length is one for all financial markets, but it is chosen as two in Thailand market.

[42] Volatility series has been stacked from each GARCH(1,1) volatility series by the sub-sample periods.



Note: These series are conditional standard deviation

Fig. 4.1. Volatility.

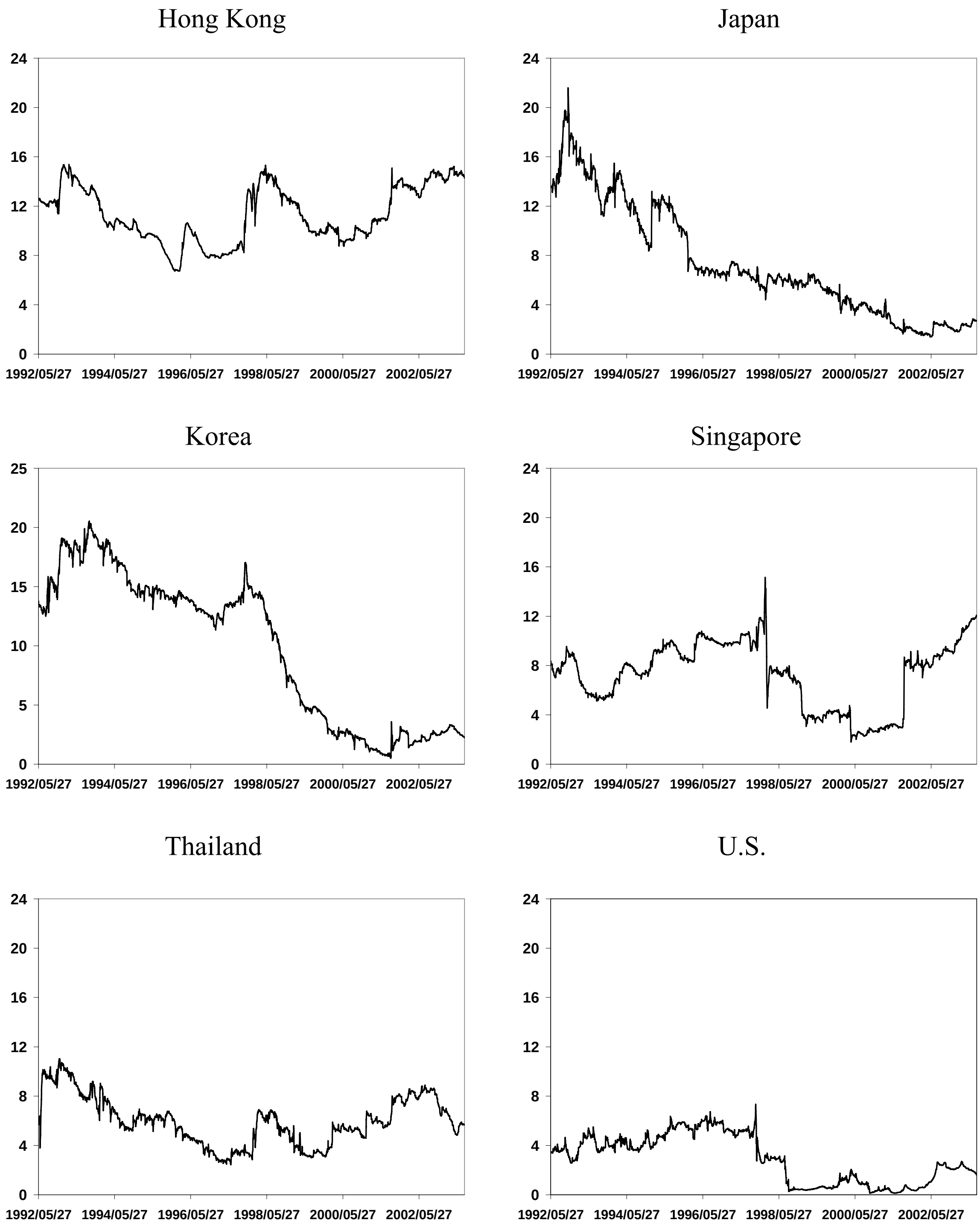


Fig. 4.2. LM statistics (joint hypothesis test).

Specifically, Hong Kong has had three structural changes in volatility since the beginning of 1990: (11/2/1993, 7/31/1996, and 12/30/1997). The possible reason of the first structural change (11/2/1993) is due to monetary policy change. Hong Kong Monetary Authority (HKMA) was found on April 1993 in Hong Kong from consolidation of the Office of the Exchange Fund and the Office of the Commissioner of Banking. It has an important role in maintaining foreign exchange rate, managing foreign reserves, keeping banking system safe, and constructing the financial infrastructure. The second change (7/31/1996) and the third change are due to the Asian crisis and the corresponding policy changes. After the middle of 1997, the currency value in Hong Kong falls and the stock market becomes more volatile. At that time, HKMA raised overnight rates from 8%to 23% on August 15, 1997 and used the policy of a pegged currency based on enough foreign reserve (more than $80 million) in October 1997 to defend local currency effectively. Also, Hong Kong raised the transparency and competitiveness of its financial market in June 2000 through initiating the Hong Kong Exchanges and Clearing (HKEX) which is the holding company of the Stock Exchange of Hong Kong Limited.[43] The HKMA announced that the final phase of interest rate deregulation covering Hong Kong's dollar savings and current accounts was in force starting July 3, 2001 so that all kinds of interest rates can be determined by competitive market power. The continued deregulation policies in the financial markets of Hong Kong appear to reduce uncertainty and risk dramatically with respect to volatility behaviors.

[43] Hong Kong Futures Exchange Limited and Hong Kong Securities Clearing Company Limited.

Japan, the second largest economy in the world, had a single structural change in volatility on 10/6/1992. Economic growth had been slowed in the 1990s after the economic bubble burst due to excess investment in the stock market and real estate during the 1980s. The possible reason of the change point (10/6/1992) arises from Japan bubble burst. Suzuki (1997) reports that Japan's financial system and markets have been suffering from both instability and inefficiency since 1992 when the economy plunged into a long balance-sheet recession triggered by the bursting of asset price bubbles. Any other structural change point implying dramatic recovery in Japan's financial market has not been detected by this test. Moreover, the results imply that the Asian crisis had an insignificant impact on the volatility structure of Japan's financial market.

Korea also experienced two structural changes in volatility: one on 12/16/1994 and one on 6/28/1996. During the first half of the 1990s, Korea's economic growth rate slowed down and the balance of payment showed a growing deficit. At this time, managerial conditions in enterprises were getting weak, as shown by reduced normal operating profit rate.[44] In addition to these problems, international affairs (the Gulf war, Japan's bubble economy) have a significant effect on prediction of the structure of volatility. After President Kim announced a five-year financial sector reform program in June 1993 (mainly for financial liberalization), and confirmed this reform announcement in late 1993, those policies acted as positive signals in the Korean financial market with respect to removing uncertainty. This was effective during the period between the two structural change points. However, prior to the prevailing bankruptcies in Korea at the

[44] See Korea Labor & Society Institute (2001).

end of 1996 or very early in 1997, the third structural change point (6/28/1996) was revealed. Even if the Korean financial market has been influenced by speculative attack in 1997, the market has shown evidences of steady recovery, as noted by successful repayment of the IMF fund, significantly positive balance of payment and continuous economic reform. That is, uncertainty and risk in the Korea financial market have been reduced gradually rather than through a big jump.

Singapore has experienced three structural changes in volatility (3/20/1991, 8/7/1997, and 1/29/2004). After the Singapore financial market had its first change point (3/20/1991) from uncertainty factor mainly due to the Gulf war and Lain American crisis in the beginning of the 1990s, the market calmed down until the Asian crisis in 1997. Guan (2002) suggested that several international shocks, including Gulf War and Asian crisis affected the Singapore economy. The economy appeared not to be vulnerable to the event, showing instantaneous recovery from the Asian crisis with a high economic growth rate (9% in 2000), but volatility in Singapore's financial market still fluctuated due to remaining uncertainty, risk, economic recession in 2001, slowdown in the worldwide economy in the beginning of 2000, and the effect of Severe Acute Respiratory Syndrome (SARS) during 2003. Then, the Singapore market recovered in 2004, shown by its economic expansions with its major traders: the U.S., EU, China, and Japan. Also, as the United States-Singapore Free Trade Agreement became effective[45] at the beginning of 2004, recovery was accelerated in Singapore economy. This caused the third structural change (1/29/2004).

[45] This free trade agreements is in force with ten economies—Australia, Brunei, Chile, European Free Trade Association, India, Japan, Jordan, Korea, New Zealand, United States —as of 2006.

Test results shows that the Thailand financial market had no structural break in volatility since 1990. It is widely acknowledged that the Asian crisis started in the Thailand financial market. However, the null hypothesis of the Sup LM test that imposes no structural change in volatility over the entire sample size (1/1/1990 – 12/31/2005) cannot be rejected. Also, the persistently fickle behavior of Thailand's volatility shown in Fig. 4.1 supports the empirical result of Sup LM test.

The U.S. shows no evidence of a structural break in volatility by the Sup LM test because the derived statistic is 7.3533 which is less than the 90% critical value. Fig. 4.1 also supports this empirical result.

Table 4.2 shows results of the GARCH(1,1) estimations using the entire sample and sub-samples. The markets which experience structural change(s) (Hong Kong, Japan, Korea, and Singapore) tend to show decreasing ϖ (constant coefficient of volatility), decreasing α (ARCH impact coefficient), and increasing β (GARCH persistence coefficient) since 1990. Hong Kong, Japan, Korea, and Singapore show decreasing ϖ values from 0.0000476 to 0.0000006, from 0.0000092 to 0.0000027, from 0.0000209 to 0.0000018, and from 0.0000279 to 0.0000041, respectively. Also those four markets have decreasing α values from 0.2506 to 0.0474, from 0.2277 to 0.0934, from 0.1454 to 0.0550, and from 0.2704 to 0.0897, respectively. However, GARCH persistence coefficient, β, tends to increase from 0.4416 to 0.9500 in Hong Kong, from 0.7561 to 0.8901 in Japan, from 0.7707 to 0.9429 in Korea, and from 0.5972 to 0.8173 in Singapore, respectively.

Table 4.2
Coefficients in volatility equations*

		ϖ [a]	α [a]	β [a]	$\bar{\sigma}$ [b]	Kurtosis
Hong Kong	All sample period[c]	0.0000034	0.0785	0.9079	0.0159	7.61
	1/1/1990-11/2/1993	0.0000476	0.2506	0.4416	0.0124	15.78
	11/3/1993-7/31/1996	0.0000031	0.0654	0.9191	0.0141	6.20
	8/1/1996-12/30/1997	0.0000115	0.1824	0.7811	0.0177	4.80
	12/31/1997-12/3/2005	0.0000006	0.0474	0.9500	0.0153	4.55
Japan	All sample period	0.0000037	0.1217	0.8597	0.0142	4.70
	1/1/1990-10/6/1992	0.0000092	0.2277	0.7561	0.0239	5.35
	10/7/1992-12/31/2005	0.0000027	0.0934	0.8901	0.0128	4.56
Korea	All sample period	0.0000031	0.0793	0.9143	0.0219	5.11
	1/1/1990-2/16/1994	0.0000209	0.1454	0.7707	0.0158	4.60
	2/17/1994-6/28/1996	0.0000185	0.0437	0.7792	0.0102	3.22
	7/1/1996-12/31/2005	0.0000018	0.0550	0.9429	0.0297	5.69
Singapore	All sample period	0.0000036	0.1372	0.8478	0.0155	6.91
	1/1/1990-3/20/1991	0.0000279	0.2704	0.5972	0.0145	12.31
	3/21/1991-8/7/1997	0.0000146	0.2052	0.6131	0.0090	4.93
	8/10/1997-1/29/2004	0.0000097	0.1120	0.8532	0.0166	8.13
	1/30/2004-12/31/2005	0.0000041	0.0897	0.8173	0.0066	2.72
Thailand	All sample period	0.0000053	0.1121	0.8746	0.0199	4.94
U.S.	All sample period	0.0000005	0.0532	0.9425	0.0107	4.97

Note:
a: $\sigma_t^2 = \varpi + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2$.
b: $\bar{\sigma}$ is unconditional standard deviation $(\bar{\sigma} = \omega/(1-\alpha-\beta))$.
b: All sample period is from 1/1/1990 to 12/31/2005.

4.5 Conclusions

This chapter tests the stability of volatility prediction structure in selected stock markets (Hong Kong, Japan, Korea, Singapore, Thailand, and the U.S.) from 1990 to 2005. Among those, four stock markets (Hong Kong, Japan, Korea, and Singapore) show one or more structural change(s) in volatility. Those markets all have structural change in volatility during the first half of the 1990s, mainly due to the Gulf war, Japan's economic recession, and the corresponding policy change. Regardless of Japan, the other three markets show additional structural changes around the period of the Asian crisis in the mid-1990s. Empirically, Hong Kong and Singapore seem to have recovered from the Asian crisis shock more instantaneously and systematically compared to Korea, which reveals continuous but relatively slow recovery.

However, results shows that Thailand and U.S. markets have no evidence of structural change in volatility since 1990. The volatility pattern in the U.S. stock returns is the most stable with the lowest volatility values compared to other financial markets. While Thailand stock market shows no structural change in volatility after 1990, the main reason for this result seems to be different from that of the U.S. market. Volatility in Thailand stock market swings steadily with large fluctuations over the sample period. That is, Thailand's own financially instable behavior makes it difficult to detect the impact from economic events.

Consequently, after financial market liberalization, most Asian countries have experienced structural change implying an increase of mean and standard deviation in volatility. In particular, the ARCH impact coefficient implying short-run adjustment (i.e. sensitivity) from immediate past shock tends to decrease. A GARCH persistence coefficient implying a relatively long-run pattern of volatility tends to increase over time. These change patterns in coefficients might be related with the development in financial markets because each financial market depends more on its past persistent volatilities, rather than past surprises. However, a multivariate study is needed to identify such structural interpretations.

CHAPTER V

CONCLUSIONS

This dissertation investigates three related issues on building empirical time series models for financial markets, (1) information transmission among U.S. nation-wide industries using stock returns, (2) REITs dynamics with macroeconomic variables considering structural break, and (3) structural change in volatility patterns in Asian financial markets with respect to contemporaneous causality, dynamics, and structural change with an unknown change (or break) point.

In chapter II, nationwide industry information transmission among stock returns of ten sectors in the U.S. economy is examined using Directed Acyclical Graph (DAG) for analyzing contemporaneous causality and Bernanke variance decomposition for dynamics. The results show that the "Information Technology" sector is the most root cause sector among the ten sectors, contemporaneously and dynamically. The "Consumer Discretionary" and "Financials" sectors are dynamically the most dependent sectors. Because test results provide that the causal structure in *ex ante* forecast innovations is not different from the causal structure in *ex post* innovations, we conclude that DAG analysis on the two methods is not affected by *ex post* and *ex ante* innovations. The empirical evidence supports innovation accounting based on DAG using *ex post* innovations. Clearly, researchers' efforts are less complicated if within-sample-fit gives the same result as out-of-sample-forecast in the study of contemporaneous innovations.

Here I demonstrate that this is the case for recent data on U.S. equity aggregates. Whether this same result holds in other cases we have nothing to say. If further research efforts are able to demonstrate similar results, researchers may place more confidence in the less complicated, within-sample-fit, procedures.

In chapter III, the contemporaneous/dynamic behavior of real estate returns and stock returns taking into account behaviors of several related macroeconomic variables is examined to understand recent movements of both returns different from investors' prediction. It is possible that a structural break has occurred in recent years. Econometric models can better determine the underlying dynamics to help understand the implied differences of returns to real estate and stocks when the structural breaks are correctly specified. Based on Chen *et al.* (1986), a structural break test is used to investigate existence of possible structural break in REITs model. Previous studies just assumed a date for the structural break or searched for the structural break using non-comprehensive tests.

Innovation accounting, focusing specifically on real estate and stock returns, shows significantly positive responses of real estate returns due to an initial shock in default risk but insignificant responses due to innovation in stock returns. Also, a shock to short-run interest rates affects real estate returns in a significantly negative direction but not stock returns. Comparison of contemporaneous causal relationships divided by structural break enables us to identify REITs in the U.S. economy with respect to causal flow. It has been discovered that both return rates may show different movements based on relationships with other macroeconomic circumstances. When investors try to build portfolios, these results provide good information for understanding financial alternatives and forecasting future movements of those investments.

In chapter IV, the stability of volatility structure in selected stock markets (Hong Kong, Japan, Korea, Singapore, Thailand, and the U.S.) is tested using data from 1990 to 2005. Among those, four stock markets (Hong Kong, Japan, Korea, and Singapore) have experienced one or more structural change(s) in volatility. The possible reasons of those structural breaks seem to be Japan's economic recession, the Asian crisis, recovery, and corresponding monetary policy change from these events. In particular, the ARCH impact coefficient implying short-run adjustment from immediate past shock has been decreased. And the GARCH persistence coefficient implying movement of the conditional variance away from its long-run mean has been increased. However, results shows that the Thailand and U.S. markets have no evidence of structural change in volatility since 1990. These patterns of coefficient changes in GARCH representation might be related with development in financial market. However, it is necessary to build a multivariate model rather than univariate model for explaining it.

Each chapter in this dissertation has limitations. In chapter II, the empirical evidence which provides homogeneity between *ex ante* and *ex post* innovations is applicable only to the U.S. stock market. Other markets are not considered here. In chapter III, the REITs model has a limited number of variables in econometric system. Other variables which are statistically and theoretically effective in building model should be considered. In chapter IV, univariate GARCH model is applied rather than multivariate GARCH model.

When increasing international financial market integration is considered in the study, multivariate model may generate more information.

The following three issues remain open and call for additional research:

(1) For chapter II, further research topic is to test structural change in causalities among sectors.

(2) For chapter III, there are two possible topics for further research. One is to investigate dynamics of other investment alternatives. The other suggested topic is research related to the predictability of the stock market, specifically, why stock returns respond significantly to their own and term spread shocks rather than other macroeconomic shocks.

(3) For chapter IV, further research is needed to expand this univariate analysis to a multivariate analysis which reflects recent market integration.

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Publications:

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