# Pacific Basin Working Paper Series

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September 2001

# FACTOR ANALYSIS OF A MODEL OF STOCK MARKET RETURNS

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## Abstract

A dynamic latent factor model of stock market returns is estimated using simulation-based techniques. Stock market volatility is decomposed into common and idiosyncratic components, and volatility decompositions are compared between stable and turmoil periods to test for possible shift-contagion in equity markets during Asian financial crisis. Five core Asian emerging stock markets are analyzed – Thailand, Indonesia, Korea, Malaysia and the Philippines. Results identify the existence of shift-contagion during the crisis and indicate that the Thai market was a trigger for contagious shock transmission.

Monte Carlo experiments are conducted to compare Simulation Method of Moments and Indirect Inference estimation techniques. Consistent with the literature such experiments find that, in the presence of auto-correlation and time-varying volatility, Indirect Inference is a better method of conducting variance decomposition analysis for stock market returns than the conventional method of moments.

Keywords: contagion, simulated method of moments, indirect inference, equity markets

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## 1. Introduction

International diversification should substantially reduce portfolio risk and increase expected returns if stock markets in different countries are influenced mostly by idiosyncratic disturbances. However, if a common factor influence (or cross-market correlations) increases significantly during a crisis in one market, this can greatly undermine benefits from international diversification. This (possible) shift in relationships is referred to as "shift-contagion" because it relates to the structural change in the relationships determining returns in one stock market, induced by a shock in another market (see Edwards (2000), Forbes and Rigobon (2000), World Bank (2000)). In other words, shift-contagion is a situation where the magnitude of international shock transmission exceeds what was expected *ex ante*.[1]

Shift-contagion can be investigated by studying cross-market linkages during stable and crisis periods. A variety of different econometric techniques have been used to analyze cross-market linkages: correlation analysis, cointegration analysis, GARCH models and probit models. The most popular method of measuring linkages between markets is correlation analysis. While, correlation analysis can give some idea about the relationships between markets, there are several problems with this method. The most prevalent problems relate to omitted variables, endogeneity and heteroskedasticity (see discussion of issues related to correlation analysis in Forbes and Rigobon (2000) and Corsetti et al (2001)). Forbes and Rigobon (1999) suggest use of an adjustment for heteroskedasticity. However, their approach makes strong simplifying assumptions that question the validity of such results. In the presence of endogeneity and omitted variables, heteroskedasticity-adjusted correlation coefficients are not an accurate measure of true correlation. In addition to the above issues the correlation method of measuring contagion is unreliable for small samples (Dungey and Zhumabekova, 2000).

This paper proposes and discusses an alternative method to conduct shift-contagion analysis in equity markets – latent factor analysis and variance decomposition of stock market returns using simulation-based estimation techniques. The first advantage of this method is that the model is specified in terms of latent idiosyncratic and common factors, which allows us to avoid the problem of omitted variables. Second, we can quantify the contribution of idiosyncratic and common shocks to the volatility of stock market returns. Third, using simulation-based techniques, namely Simulation Method of Moments and Indirect Inference, allows us to impose a GARCH structure on the factors of the model to eliminate the problem of conditional heteroskedasticity detected in daily stock market returns.

The objective of this paper is to investigate the properties of the proposed estimation methods and to apply it to the analysis of shift-contagion during the Asian crisis of 1997. This paper draws upon work of Gourieroux et al (1993), Gallant and Tauchen (1996), Dungey, Martin, and Pagan (2000) and Dungey and Martin (2000).

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[1] This definition is consistent with the epidemiological definition, which says that contagion is present when any disease or event occurs in clear excess of normal expectancy (Edwards, 2000:5).

The paper is organized as follows. Section 2 discusses and investigates the properties of stock market return data utilized in the analysis. Section 3 outlines the latent factor model of stock market returns with AR and GARCH specifications. Section 4 provides a discussion of appropriate estimation techniques. The algorithm and auxiliary models for SMM and Indirect Inference estimators are provided in Sections 5 and 6 respectively. Section 7 reports and analyses the parameter estimation results. Section 8 describes the set up and results of the Monte Carlo experiment comparing SMM and Indirect Inference estimators. Based on the results of the Monte Carlo experiments, this paper focuses on the analysis of the variance decomposition results based on the Indirect Inference estimated parameters, and this analysis is provided in Section 9. Section 10 describes a factor extraction procedure using a Kalman filter and its results. In Section 11 the standard errors of the factor contribution are estimated using the bootstrapping technique, and the formal test for shift-contagion is conducted. Section 12 provides concluding remarks.

## 2. Properties of stock market return data

The data utilized in the empirical analysis includes equity price indices compiled by Thomson Financial Datastream for the following markets: Thailand, Indonesia, Korea, Malaysia and Philippines. All data is in US dollars. When evaluating shock transmission in a regional context, we are interested in the behavior of investors moving money between markets or in reacting to events in other markets. Global investors must take into account both movements in the exchange rate and underlying stock price, priced in local currency. Since USD is the best proxy for a global currency, we use stock market returns denominated in the US dollars. Further support for use of US dollar returns in this analysis is from Bae et al (2000) and Forbes and Rigobon (1999). In their empirical studies of contagion they both find little difference in results between use of local currency and USD denominated stock market returns.

The returns on the equity price indices are calculated as a log-difference of the equity prices. Additionally the returns are centered to zero to ease the convergence of the optimization process.

Since all the markets in this analysis are located in the same region, we do not face time zone issues, which otherwise might affect the results.

To identify a shift-contagion in these markets during the East Asian financial crisis, two periods are defined as stable and crisis periods. The period of relative stability is defined as from December 29, 1994 through to March 31, 1997. The sample contains 587 observations. The period of turmoil is defined as from June 1, 1997 through to August 31, 1998, containing 326 observations. The turmoil period contains the period of crisis in the Thai stock market, Korean stock market and Indonesian stock market. Charts 1 (a)-(e) show the stock market returns for each markets analyzed in this paper. Though it is clear from the charts that most of the Asian markets experienced turmoil of different degrees starting in May 1997, the question as to how to determine the start of the stock market crisis remains disputable. Although the start of the Asian financial crisis is often defined as July 2,

1997,with the devaluation of Thai baht, Asian stock markets started to experiences high volatility earlier (see Kaminsky and Schmukler (1999), and Dungey and Martin (2000)). Therefore, the end of the period of relative stability is defined as March 31, 1997 to avoid including the turmoil observations in the stability period analysis. Charts 1(a)-(e) and Table 1 illustrate that during the period of relative stability defined in this analysis the fluctuations in the stock market returns are small relative to the crisis period.

Table 1 provides some characteristics of the examined stock index data. Summary statistics include the mean of the time-series, standard deviation, minimum and maximum of the daily stock market returns, their skewness and kurtosis. The standard deviation in Asian emerging markets increased by 3 to 5 times between the stable and turmoil periods. Minimum daily changes in Indonesian and Korean stock markets reached -18.6% and -11.8% respectively during the turmoil period compared with –4% and –4.4% during the stable period, on average minimum daily moves increased by 3 times. Maximum daily moves in Asian emerging stock markets reached on average 17% during the crisis relative to 4% during the stable period.

Descriptive statistics of stock market returns in Table 1 demonstrate that all return series exhibit non-normality.

A well known property of high frequency (daily) financial market return data is the time varying nature of the second moments (Mills, 1993). The overwhelming empirical evidence of conditional heteroskedasticity in high-frequency financial return series is demonstrated in the literature survey by Bollerslev et al (1992). Since in this analysis I use daily stock market returns, the GARCH(p, q) properties of the data are investigated. High-frequency financial data are also known to exhibit an autoregressive property. Hence, univariate AR(1) and ARCH(1), and AR(1) and GARCH(p, q) models of stock returns are estimated with the maximum lag order of the squared error term and the unconditional variance chosen as 2. The above models are estimated over the period from January 1, 1995 to March 31, 1997 – the relatively stable period. The form of the GARCH model for five stock market returns $s_{i,t}$, where $i$ = *Thailand, Indonesia, Korea, Malaysia, Philippines* is:

$$s_{i,t} = r_0 + r_1 s_{i,t-1} + e_{i,t} \quad ,$$

$$e_{i,t} = \sqrt{h_{i,t}} u_{i,t},$$

$$h_{i,t} = a_0 + a_1 \sum_{l=1}^{p} h_{i,t-l} + b_1 \sum_{k=1}^{q} e_{i,t-k}^2$$

$$u_{i,t} \sim N(0,1)$$

Table 2 reports Akaike information criterion (AIC) and Schwarz-Bayesian criterion (BIC) for alternative GARCH(p, q) fitted models.

When using the AIC for most of the stock markets the GARCH(1,2) specification is selected (see Table 2). When using BIC the GARCH(1,1) is selected. For this analysis the specification GARCH(1, 1) is chosen to avoid the over-parameterization of the model and to reduce the computation time.

Results in Table 3 provide strong evidence of first order autocorrelation in the stock market returns and significant first order GARCH effects for all stock market returns considered during both stable and crisis periods.

## 3. Latent Factor Model of Stock Market Returns

Early literature on the linkages between financial markets following the US stock market crash of October 1987 introduced a factor model of stock returns. In this model, idiosyncratic factors and common factors explain movements in stock prices. King and Wadhwani (1990) were the first to propose a model of stock markets returns as a linear function of idiosyncratic, or country-specific, and common, or systematic, factors:

$$ s_{i,t} = \boldsymbol{f}_i C_{i,t} + \boldsymbol{l}_i W_t \qquad\qquad i = 1,...N \qquad\qquad (1) $$

where $C_{i,t}$ represents information at time $t$ that affects the specific market $i$ only, and $W_t$ is the common factor that represents the information affecting all stock markets at time $t$. Parameters $\varphi_i$ and $\lambda_i$ are market $i$ specific but do not change over time, unless a structural shift in the relationships occur.

Later literature (Lin, Engle and Ito (1994), King, Sentana and Wadhwani (1990)) exploit the linear model (1) as a basic model of stock returns to develop a conditional factor model and examine the links between world stock markets and the transmission of volatility from one market to another. Recently, Dungey and Martin (2001a) and Dungey(1999) applied the unconditional factor model to modeling the volatility of the exchange rates and examining the contagion in the East Asian currency markets of 1997 using GMM, and Dungey and Martin (2001b) utilized a conditional factor model to investigate the extent of spillovers and residual contagion across financial markets during the East Asian financial crisis.

The 2-factor model can be extended further. For example, in the case including the markets located outside Asia-Pacific region, a region-specific factor can be added to specification to distinguish between factors commonly affecting markets located in one region from the factors affecting commonly all markets in the system (see, for example, Dungey, Fry, and Martin (2001) and Kose, Otrok, and Whiteman (1999)). Another possible extension of the model is to include a market-specific factor. For example, a Thai factor can be included to analyze the contribution of Thai market in the volatility of other markets in the system. Finally, idiosyncratic and/or common factors can be further decomposed into two components – an unobserved factor and an observed factor (see, for example, Dungey (1997) and Aruman (2001)).

Since analysis of the data gives strong evidence of first order autocorrelation and significant first order GARCH effects for all stock market returns considered in our analysis, this paper incorporate an AR(1) and GARCH(1,1) processes in the latent factor model. Diebold and Nerlove (1989) for their analysis of volatility of exchange rate returns, and King, Sentana and Wadhwani (1990) for their analysis of volatility of stock market returns impose an ARCH(1) structure on the unobserved factors. However, Harvey, Ruiz and Sentana (1991)

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with the help of Monte Carlo experiments demonstrate that the addition of the lagged conditional variance is needed to obtain a better estimator.

To eliminate the problem of conditional heteroskedasticity detected in the daily stock market returns GARCH could be specified for each latent factor of model (1). For example, Lin, Engle and Ito (1994) impose a GARCH structure on both global and local factors. However, Dungey, Martin and Pagan (2000) show that the GARCH characteristic of the high-frequency financial data is driven by common factors, and, hence, can be sufficiently captured by placing a GARCH structure on the common factor. Therefore, common factor $W_t$ is assumed to have auto-regressive representation with GARCH conditional variances:

$$W_t = r\, W_{t-1} + e_t \qquad\qquad (2)$$

$$e_t = \sqrt{h_t}\, u_t \qquad\qquad (3)$$

$$h_t = a_0 + a\, e_{t-1}^2 + b h_{t-1} \qquad\qquad (4)$$

$$u_t \sim N(0,1) \qquad\qquad (5)$$

Following Diebold and Nerlove (1989) $\alpha_0$ in equation (4) is restricted as:

$$\alpha_0 = 1 - \alpha - \beta \qquad\qquad (6)$$

to normalize the unconditional variance of the common factor to $1/(1 - r^2)$.

The model we estimate then is defined by equations (1) – (5) including restriction (6). The country factors $C_{i,t}$ are specified to be normal random variables with constant variances. All factors are specified to be independent. We specify model (1) – (6) for 5 Asian emerging stock markets: Thailand, Indonesia, Korea, Malaysia and Philippines. The model has 13 parameters - $f_i$ , $l_i$ , (i=T,I,K,M,P), $r$ , $a$ and $b$ . Parameters form vector $q$ .

## 4. Simulation-based estimation technique

Direct estimation of model (1) is difficult due to factor identification problems (Forbes and Rigobon, 2000). $C_i$s and W can be variables related to trade, finance, economic and political news. However, it is impossible to say with certainty what variables (or sets of variables) identify country-specific or common factors. A few empirical studies made an attempt to use news as the proxies for idiosyncratic and common shocks. Kaminsky and Schmukler (1998) use a set of dummies that represent local and neighbor-countries news to identify what triggered sharp movements in stock prices during the East Asian financial crisis. They find that some of the large changes in stock prices cannot be explained by any apparent substantial news. Baig and Goldfajn (1998) study the impact of own country-news (as a proxy for idiosyncratic shocks), and S&P 500 returns and Yen-dollar exchange

rate (as proxies for common shocks) on the financial markets of five Asian economies – Thailand, Malaysia, Korea, Indonesia and Philippines. Their conclusion is similar to that of Kaminsky and Schmukler's (1998). The difficulty of making identification assumptions about the factors determining the model remains the main limitation to empirical work.

One way to proceed with estimation of the latent factor model is to assume factor independence and normalize the variance of the latent factors to 1. This normalization means that the estimated parameters will absorb the true variances of the unobserved factors, for example, the estimate of the parameter $\boldsymbol{f}_i$ will be in fact an estimate of $\boldsymbol{f}_i \sqrt{\operatorname{var}(C_i)}$. Hence, while the parameters of model (1) during the periods of relative stability and crisis cannot be compared directly, each factor's contribution to the volatility of the equity index can be measured as:

$$cont(C_i)_i = \frac{\boldsymbol{f}_i^2 \operatorname{var}(C_i)}{\operatorname{var}(s_i)} = \frac{\boldsymbol{f}_i^2 \operatorname{var}(C_i)}{\boldsymbol{f}_i^2 \operatorname{var}(C_i) + \boldsymbol{l}_i^2 \operatorname{var}(W)}$$  - contribution of the idiosyncratic factor

$C_I$ to volatility of equity index $i$;     (7)

$$cont(W)_i = \frac{\boldsymbol{l}_i^2 \operatorname{var}(W)}{\operatorname{var}(s_i)} = \frac{\boldsymbol{l}_i^2 \operatorname{var}(W)}{\boldsymbol{f}_i^2 \operatorname{var}(C_i) + \boldsymbol{l}_i^2 \operatorname{var}(W)}$$  - contribution of the common factor $W$

to volatility of equity index $i$.     (8)

and compared between two periods.

In this interpretation the true variance of the factor does not distort the conclusion, and the significant change in factor contributions between the periods of stability and crisis will indicate the shift-contagion.

The model without AR and GARCH characteristics can be estimated using GMM. Using this technique the estimates of the model (1) parameters, which embody the standard deviations of latent factors, can be obtained by matching the second moments of the data with those of the model. However, the complexity of the latent factor model (1 -5) with AR(1) and GARCH(1,1) structures does not allow us to employ GMM to estimate the model parameters. Maximum likelihood estimation of the model is not feasible because analysis of the dynamic latent variable model would involve integration over the unobserved realization of the state vector, which is computationally infeasible. An alternative estimation method is the Kalman filtering method (see Harvey and Shepard (1994) and Kim et. al. (1994). Kalman filtering yields asymptotically efficient estimates in the special case when only AR structures are imposed on the latent factors, however, as shown in Gourieroux and Monfort (1994) it does not necessarily achieve consistency when the latent factors exhibit GARCH structures.

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The ability to simulate the series of observed variables in model (1-6) allows us to use a variety of simulation-based procedures to estimate the model. These procedures include: (i) the simulated method of moments (SMM) of Duffie and Singleton (1993), (ii) the indirect inference estimator, proposed by Smith (1993) and further developed by Gourieroux et al (1993), and (iii) the efficient method of moments (EMM) proposed by Bansal et al. (1995) and developed in Gallant and Tauchen (1996).

Simulation techniques have been applied extensively to estimate the stochastic volatility model of asset returns (see, for example, Duffie and Singleton (1993), Gourieroux et al (1993), Gallant et al. (1997)). Ohanian et al. (1997) use simulation-based techniques to estimate a non-linear production function with latent factors. Recently Dungey et al. (1999) used Indirect Inference to conduct a latent factor decomposition of volatility in bond spreads; and Dungey, Fry and Martin (2001), Dungey and Martin (2001b) applied SMM techniques to investigate contagion in currency and equity markets.

The basic idea of each of these techniques is to calibrate parameters to get similar characteristics for the observed endogenous variables and for the simulated ones. This is done through the use of an auxiliary model, or score generator, that captures the properties of the observed data. The choice of the auxiliary model is discussed in the subsequent section.

Consider three simulation-based estimators on the following dynamic model:

$$y_t = f(\boldsymbol{q}, y_{t-1}, x_t, f_t, e_t) \qquad\qquad \text{t=1,...,T}$$

$$e_t \sim N(0,1)$$

where $y_t$ is a set of observed dependent variables, $\boldsymbol{q}$ is a vector of structural parameters, $f_t$ is a vector of factors – observed and unobserved, determining $y_t$, $x_t$ is a set of observed exogenous variables, $e_t$ is a white noise.

In these three methods the vector of estimated parameters $\hat{\boldsymbol{q}}$ of the latent factor model is empirically determined as:

$$\hat{\boldsymbol{q}} = Arg \min_{\boldsymbol{q}} D'\Omega D$$

where $\boldsymbol{W}$ is the optimal weighting matrix. The estimators differ in the choice of $D$.

Assume it is possible to simulate values of $y_t$ for a given initial condition and a given value of parameters $\theta$, conditional on an observed path of exogenous variables $x$.

Let $Q(Y_{[T]}, \beta)$ be the objective function associated with the auxiliary model using actual data of length $T$, and $Q(\tilde{Y}_{[TH]}, \boldsymbol{b})$ be the objective function for the same auxiliary model, but evaluated with the simulated data of the length $T*H$. In the case of Indirect Inference, parameters of the auxiliary model $\hat{\boldsymbol{b}}$ are estimated as a maximand of the objective function $Q(Y_{[T]}, \beta)$. Then simulated data from the true model is used to obtain a maximand $\tilde{\boldsymbol{b}}$ of

the objective function $Q(\widetilde{Y}_{[TH]}, \beta)$. The Indirect inference estimator $\boldsymbol{q}$ is defined as a solution of a minimum distance problem (Gourieroux et al , 1993):

$$\boldsymbol{q} = \underset{\boldsymbol{q}}{\text{Argmin}} \left[ \hat{\boldsymbol{b}}_T(Y_{[T]}) - \widetilde{\boldsymbol{b}}_{TH}(\widetilde{Y}_{[TH]}, \boldsymbol{q}) \right]' \hat{\Omega}_T \left[ \hat{\boldsymbol{b}}_T(Y_{[T]}) - \widetilde{\boldsymbol{b}}_{TH}(\widetilde{Y}_{[TH]}, \boldsymbol{q}) \right] \qquad (9)$$

In other words we match the parameters maximizing the objective function evaluated at the actual data with the parameters maximizing the objective function evaluated with the simulated data.

The EMM estimator (see Gallant and Tauchen, 1996) chooses $\boldsymbol{q}$ such that the distance between the gradient of the objective function for the auxiliary model (or auxiliary scores) evaluated with the true data and auxiliary scores evaluated with simulated data, is close to zero:

$$\boldsymbol{q} = \underset{\boldsymbol{q}}{\text{Argmin}} \left[ \frac{\partial Q(Y_{[T]}, \boldsymbol{b})}{\partial \boldsymbol{b}'} - \frac{1}{TH} \sum_{t=1}^{TH} \frac{\partial Q(\widetilde{Y}_{[TH]}, \boldsymbol{b})}{\partial \boldsymbol{b}'} \right]' \hat{\Omega} \left[ \frac{\partial Q(Y_{[T]}, \boldsymbol{b})}{\partial \boldsymbol{b}'} - \frac{1}{TH} \sum_{t=1}^{TH} \frac{\partial Q(\widetilde{Y}_{[TH]}, \boldsymbol{b})}{\partial \boldsymbol{b}'} \right] \quad (10)$$

Therefore, instead of calibrating the auxiliary parameters as in Indirect Inference, in EMM we calibrate the auxiliary scores.

Gourieroux et al (1993) show that in a special case where there are no exogenous variables and the auxiliary model corresponding to the pseudo-likelihood function is asymptotically well specified, Indirect Inference and EMM estimators are asymptotically equivalent.

SMM is a simulation technique, where to obtain the estimates of the parameters we simply match the moments based upon the actual and simulated data. Gourieroux et al (1993) demonstrates that the SMM estimator is a special case of the Indirect estimator, where there are no exogenous variables and the auxiliary model is specified as a vector of empirical moments that capture the specific characteristics of the observed data. In this case, $\hat{\boldsymbol{b}}_T = \frac{1}{T} \sum_{t=1}^{T} m(Y_t)$ and $\widetilde{\boldsymbol{b}}_{TH} = \frac{1}{TH} \sum_{t=1}^{TH} m(\widetilde{Y}_t)$. Hence, the estimator of the model parameters is obtained as a solution minimizing:

$$\boldsymbol{q} = \underset{\boldsymbol{q}}{\text{Argmin}} \left[ \frac{1}{T} \sum_{t=1}^{T} m(Y_t) - \frac{1}{TH} \sum_{t=1}^{TH} m(\widetilde{Y}_t) \right]' \hat{\Omega}_T \left[ \frac{1}{T} \sum_{t=1}^{T} m(Y_t) - \frac{1}{TH} \sum_{t=1}^{TH} m(\widetilde{Y}_t) \right] (11)$$

Michaelides and Ng (2000) assess the finite sample properties of the three simulation-based methods using Monte Carlo experiments. They conclude that SMM tends to have larger biases and variances than Indirect Inference and EMM, but is easiest to implement. With large samples and when the auxiliary model encompasses as many features of the data as possible, the efficiency of EMM and Indirect Inference estimators approach that of Maximum likelihood estimator (MLE), where MLE exists. They also find that EMM is more sensitive to the choice of the auxiliary model than Indirect Inference Estimator.

Since the estimated model does not have exogenous variables and the samples analyzed are large, the Indirect Inference and EMM will produce equivalent estimates. Additionally, the computationally demanding nature of the model (1) – (6) implies the need in a simple auxiliary model. Michaelides and Ng (2000) demonstrate that with a simple auxiliary model Indirect Inference is the most accurate estimator in terms of biases in estimated parameters. Hence, Indirect Inference is the preferred technique to estimate the parameters of model (1) – (6).

The choice of the Indirect Inference estimator is also consistent with other empirical work in this area, including Michaelides and Ng (2000), Gallant and Tauchen (1996), Gallant et al.(1997), who evaluate the relative efficiency of simulation-based estimators using relatively simple models of time-series. They find that the Indirect Inference estimator outperforms the conventional method of moments. Therefore, Indirect Inference will be utilized as one of the simulation-based techniques to estimate the latent factor model. Additionally, this paper will estimate the latent factor model using SMM and compare the empirical results of two estimation methods. Furthermore, to assess the statistical properties of two estimators the Monte Carlo experiment utilizing the structural model (1) – (6) will be conducted in Section 8.

## 5. Methodology of the SMM Estimation

### 5.1 Auxiliary model

Identification requires that the dimension of the auxiliary model at least exceeds that of the structural parameter vector $q$, but otherwise the auxiliary model need not have anything to do with the structural model. However, as with any GMM-based procedure, the choice of auxiliary model is very important for efficiency (Andersen et al., 1999). As demonstrated in Michaelides and Ng (2000) for SMM to produce efficient estimators, the auxiliary model should adequately capture the characteristics of the data. Following the approach by Dungey and Martin (2000) and Dungey, Fry, and Martin (2001), this paper uses the following three sets of moment conditions as a part of auxiliary model. The first set of conditions consists of variances and covariances of five stock market returns :

$$m_{ij,t}^{(1)} = s_{i,t}s_{j,t}, \qquad i \geq j, \quad i,j = T,I,K,M,P, \qquad (12)$$

The second and third sets of moment conditions are chosen based on the property of the data that stock market returns are characterized by strong first-order autocorrelation in the means and variances. Therefore, the second set of moment conditions is obtained by taking the auto-covariances of five stock market returns:

$$m_{i,t}^{(2)} = s_{i,t}s_{i,t-1}, \qquad i = T,I,K,M,P \qquad (13)$$

The third set consists of auto-covariances of squared stock market returns, defined as:

$$m_{i,t}^{(3)} = \left(s_{i,t}^2 - \bar{s}_{i,t}^2\right)\left(s_{i,t-1}^2 - \bar{s}_{i,t}^2\right), \qquad i = T,I,K,M,P \qquad (14)$$

Additionally, the fourth set is included, which is the set of the fourth moments – kurtosis, to account for non-normality of returns:

$$m_{i,t}^{(4)} = \left( \frac{s_{i,t} - \bar{s}_i}{\hat{\boldsymbol{s}}_i} \right)^4, \qquad i = T, I, K, M, P \qquad (15)$$

Combining all 4 sets of moment conditions into the (TT x 30) matrix:

$$M = \begin{bmatrix} m_{ij,1}^{(1)} & m_{i,1}^{(2)} & m_{i,1}^{(3)} & m_{i,1}^{(4)} \\ m_{ij,2}^{(1)} & m_{i,2}^{(2)} & m_{i,2}^{(3)} & m_{i,2}^{(4)} \\ ... & ... & ... & ... \\ m_{ij,TT}^{(1)} & m_{i,TT}^{(2)} & m_{i,TT}^{(3)} & m_{i,TT}^{(4)} \end{bmatrix}_{TTx30} \qquad (16)$$

Taking the sample means of all sets of moments yields $\frac{N(N+1)}{2} + 3N$ moment conditions $\bar{m}$. In our analysis of 5 stock markets there are 30 moment conditions and 13 parameters in the structural model. Therefore, the system is over-identified.

## 5.2 Algorithm

SMM simply matches the expected values of the moments (12) – (15) based upon the actual and simulated data. The parameter estimates are obtained as a solution to the minimization problem (11). To simulate the series of stock market returns of the length TT*H, where TT is the number of observations in the sample of observed data and H is number of simulation paths, we follow steps (1) to (2):

Generate a set of random numbers for $u_{w,t}$ from $N(0,1)$ distribution, which enters the equation (3) and $C_{i,t}$, where $i=T, I, K, M, P,\ t = 1,..,TT*H$.

Choose starting values for $\boldsymbol{q}$. Simulate stock market returns $s_{i,t}^{sim}$ for $i=T, I, K, M, P$ and $t = 1, .., TT*H$, using the structural model (1) – (6) with a set of chosen parameter values $\boldsymbol{q}$.

The weighting matrix $\hat{\Omega}_T$, which enters equation (11) is calculated using the observed data as:

$$\hat{\Omega}_T = \left[ \frac{1}{TT} \Gamma_t' \Gamma_t + \frac{1}{TT} \sum_{k=1}^{K} \left( 1 - \frac{k}{K+1} \right) \left( \Gamma_t' \Gamma_{t-k} + \Gamma_{t-k}' \Gamma_t \right) \right]^{-1} \qquad (17)$$

where:

$$\Gamma_t = M_t - \bar{m},$$

$M_t$ is the $t$-th row of the matrix of moments $M$, K is the maximum number of lags used in the Newey-West

weights $\left(1 - \dfrac{k}{K+1}\right)$ to control for auto-correlation of the residuals.

The variance matrix of the estimated parameters is given by:

$$W_H = \left(1 + \frac{1}{H}\right) * \left( E\left[\frac{\partial m'}{\partial \boldsymbol{q}}\right] * \hat{\Omega} * E\left[\frac{\partial m}{\partial \boldsymbol{q}}\right] \right)^{-1} \tag{18}$$

## 6. Methodology of the Indirect Inference Estimation

### 6.1 Auxiliary Model

A discussion of different approaches to the choice of auxiliary model is found in Dungey, Martin, and Pagan (2000). One approach is to choose the auxiliary model in such a way that it would deliver estimators, which are as efficient as the maximum likelihood estimators if the latter could be found. An alternative approach chooses an auxiliary model such that the "stylized facts" implicit in the auxiliary model are meaningful to an investigator. We will follow the second approach.

The choice of equations for the auxiliary model follows Dungey, Martin, and Pagan (2000), and is based on the properties of the data analyzed in section 2.

The first set of equation for the auxiliary model will consist of the vector of second central empirical moments – variances and co-variances of stock market returns:

$$\boldsymbol{b}_{ij,t}^{(1)} = s_{i,t} s_{j,t}, \quad i \geq j$$
$$i,j = T, I, K, M, P \tag{19}$$
$$t = 1, .., TT$$

where TT is the number of observations in the sample.

Taking the sample means yields total $n*(n+1)/2 = 5*(5+1)/2 = 15$ parameters $\boldsymbol{b}_{ij}^{(1)}$.

Stock market returns are characterized by strong first-order auto-correlation in the levels of stock market returns. Hence, the second set of equations is represented by a VAR(1) model of the stock market returns to capture AR(1) process in the levels:

$$s_{i,t} = \boldsymbol{b}_{ij}^{(2)} s_{j,t-1} + u_{i,t}, \quad i,j = T, I, K, M, P$$
$$t = 1, ..., TT \tag{20}$$

Equations (20) produce $n^2 = 25$ parameters.

Time-varying volatility of stock market returns is captures in the third set of equations of auxiliary model represented by the VAR(1) model of squared errors of equation (20):

$$u_{i,t}^2 = \boldsymbol{b}_{0i}^{(3)} + \boldsymbol{b}_{ij}^{(3)} u_{i,t-1}^2 + \boldsymbol{e}_{it}, \quad i,j = T,I,K,M,P$$
$$t = 1,..,TT \tag{21}$$

There are $(n + n^2) = 30$ parameters from equation (21).

Overall there are 70 parameters in the auxiliary model and 14 parameters in the structural model, hence, the parameter of the structural model (1) – (6) can be estimated using the Indirect Inference technique. The algorithm of Indirect Inference estimator is described in the following section.

## 6.2 Algorithm

The idea behind Indirect Inference is that the auxiliary model is misspecified and the simulations are supposed to correct for the bias in the auxiliary model estimates induced by model specification. Correction is achieved by adjusting the parameters of the structural model such that the parameters of the auxiliary model $\hat{\boldsymbol{b}}$ estimated with the observed data match the parameters of the auxiliary model $\widetilde{\boldsymbol{b}}$ estimated with the simulated data.

The first step of the indirect estimation is to obtain the estimates $\hat{\boldsymbol{b}}$ of the model given by equations (19)-(21) using observed data of stock market returns for 5 stock markets – Thailand, Indonesia, Korea, Malaysia and Philippines.

The second step is to simulate H paths of the series of returns of the length TT, or, as in SMM estimation, the returns are simulated as one long path of length TT*H. For simulation, follow the steps (1) - (2) in Section 5.2.

The third step of indirect inference is to obtain the estimates $\widetilde{\boldsymbol{b}}$ of the structural model (19)-(21) using simulated stock market returns for 5 analyzed stock markets.

Finally, the indirect estimates of $\boldsymbol{q}$ are obtained as a solution to the minimization problem (9), where $\hat{\Omega}_T$ is the weighting matrix. The form of the weighting matrix is given in Gourieroux et al. (1993) as:

$$\hat{\Omega}_T = \left[ \frac{1}{TT} \Gamma_t{}'\Gamma_t + \frac{1}{TT} \sum_{k=1}^K \left(1 - \frac{k}{K+1}\right)\left(\Gamma'_t \, \Gamma_{t-k} + \Gamma'_{t-k} \, \Gamma_t\right) \right]^{-1} \tag{22}$$

where $\Gamma_t$ is the $t$-th row in the matrix of residuals from auxiliary model evaluated with the observed data, $K$ is the maximum number of lags. Newey-West weights $\left(1 - \frac{k}{K+1}\right)$ are utilized to control for auto-correlation.

The asymptotic variance-covariance matrix of the estimated parameters is calculated as:

$$W_H = \left(1 + \frac{1}{H}\right) * \left(\frac{\partial^2 Q}{\partial \boldsymbol{b} \partial \boldsymbol{q}'} * \hat{\Omega} * \frac{\partial^2 Q}{\partial \boldsymbol{b} \partial \boldsymbol{q}}\right)^{-1} \qquad (23)$$

## 7. Estimation Results

For SMM and Indirect Inference estimations we simulated data sets of length *50\*TT*, where *TT* is the number of observations in the sample. The maximum lag length in (17) and (22) were set at *K*=5. To minimize the Indirect Inference and SMM criterion functions (9) and (11), estimation uses the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm in OPTMUM in GAUSS. The gradient of the objective function is a convergence criterion, and the calculations are stopped when the elasticity of the gradient with respect to each parameter is less than 1.0E-3. The parameter estimates from GMM estimation of unconditional factor model are chosen for starting values of $\boldsymbol{f}_i$ and $\boldsymbol{l}_i$, (i=T,I,K,M,P). Starting values of $\boldsymbol{r}$, $\boldsymbol{a}$ and $\boldsymbol{b}$ are chosen arbitrarily. Additionally, to avoid a local minimum several estimations with different sets of starting values are conducted.

The results of the SMM estimation of latent factor model (1) – (6) are reported in Tables 4 and 5.

Table 4 contains SMM parameter estimates and their standard errors for the periods of stability and crisis. The informational content of the parameter estimates is limited since they contain the volatility of the latent idiosyncratic and common factors. However, these tables show that estimated standard errors for estimated parameters $\boldsymbol{l}_i$ and AR and GARCH parameters are very large. The problem may be in the structure of auxiliary model. This issue is investigated later in Section 8 using the Monte Carlo experiment.

Instead of comparing parameter estimates we can compare the variance decompositions of the stock market returns over two periods, which are obtained by taking the variances of both parts of equation (3.11). Taking into account the assumption that the factors are independent, that the idiosyncratic factor variance is normalized to 1, and that the unconditional variance of the common factor is normalized to be $\dfrac{1}{(1-\boldsymbol{r})^2}$, the contribution of the idiosyncratic factor *i* to the total variance of stock market *i* becomes:

$$\frac{\hat{\boldsymbol{f}}_i^2}{\hat{\boldsymbol{f}}_i^2 + \hat{\boldsymbol{l}}_i^2 / (1 - \boldsymbol{r}^2)},$$

and the contribution of the common factor to the total variance of the stock market *i* is:

$$\frac{\hat{l}_i^2 / (1 - r^2)}{\hat{f}_i^2 + \hat{l}_i^2 / (1 - r^2)}$$

The variance decompositions over the two periods are demonstrated in Table 5.

The results in Table 5 are very similar to the results of GMM estimation of the unconditional factor model without AR and GARCH processes reported in Table 6. This wouldn't be a surprise if GMM and SMM estimated the same model, with SMM utilizing a simulated data set of considerable length. For example, see Dungey et al (2000) for discussion about the relationships between GMM and SMM estimators. However, the latent factor model, specified by (1) – (6), has a significant distinction from the unconditional factor model – it incorporates AR and GARCH processes attributable to (associated with) stock market returns data. This fact could be an indication that moment conditions (12) – (15) specified for SMM do not capture fully these data characteristics. This issue will be further explored in the next section. As Duffie and Singleton (1993) emphasized, the moments should have enough variations to allow for identification of the structural parameters. Therefore, the choice of the auxiliary model can significantly affect the results of SMM estimation.

The results of the Indirect Inference estimation are reported in Table 7. As for SMM, Table 7 reports the parameter estimates for the simulation path of the length 50*TT and the asymptotic standard errors. Except for the GARCH $\beta$ parameter, all estimated parameters have small standard errors compared with SMM results.

Variance decompositions using Indirect Inference estimates are reported in Table 8. The results differ substantially from their SMM counterparts, although the direction of change in variance decompositions between periods of stability and crisis remains the same. Both SMM and Indirect Inference results indicate the increase in common factor influences on the volatility of equity markets.

Smaller standard errors estimated using the Indirect Inference method indicate that SMM is a less efficient technique when estimating the latent factor model with AR and GARCH processes. Before the discussion of the results, a Monte Carlo experiment to assess the finite sample properties of two estimators will first be conducted. The set up and results of the experiment are discussed in the following section.

## 8. A Monte Carlo Comparison of two Simulation Estimators – SMM and Indirect Inference

### 8.1 Set up of the experiment

To assess the finite sample properties of the simulated methods of moments and Indirect Inference estimators, the following Monte Carlo experiment is conducted. For each of the estimators the experiment consists of $N$ simulations. The model given by equations (1) – (6) is specified for 5 markets: *A, B, C, D, E*. The sample size for Monte Carlo experiments is *T=300*. True values of parameters of the model (1) – (6) $j_i$, $l_i, i = 1,...5$, *r*, *a* and *b* are chosen as *q*, and fixed during the simulation routine.

For the *n*-th simulation:

[1]  generate a Tx5 matrix of idiosyncratic factors $C_{i,t}$ from the standard normal distribution, generate a Tx1 vector of error terms $u_t \sim N(0,1)$;

[2]  compute the vector of observations for common factor $W_t$ as in (2)-(6) using given parameters $\rho$, $\alpha$ and $\beta$ and generated errors $u_t$;

[3]  calculate a Tx5 matrix of returns $s_{i,t}$ according to (1);

[4]  specify auxiliary model (12) – (15) for SMM, and (19) – (21) for Indirect Inference estimators;

[5]  follow the algorithm in section 5.2 to obtain SMM estimators, execute algorithm described in section 6.2 to obtain Indirect estimators;

[6]  update n and go to step (1);

[7]  when n = N, calculate the expected values of the estimated parameters and their standard errors using the results of N Monte Carlo simulations. As starting values for SMM and Indirect Inference we use the GMM estimates of the parameters $\varphi_i$, $\lambda_i$, i = 1,..5. Starting values for AR(1) and GARCH(1,1) parameters are arbitrarily chosen as {0.5, 0.3, 0.3}.

[8]  The number of simulations for SMM is set as N = 500. For Indirect Inference, the number of simulations is limited to 300 due to very long computation time.

The above Monte Carlo experiment is conducted for the different length simulations paths with *H*=20, *H*=50, and *H*=100 to investigate the sensitivity of the simulation–based estimators to the size of the simulation path.

## 8.2 Results

The results for SMM are reported in Table 9. The SMM estimator tends to slightly underestimate $j_i$ and overestimate $l_i$. However, when the estimated and true AR and GARCH parameters are compared, biases in estimated parameters are very large, accounting for more than 200% of the true values. This is not so important when one of the factors' impact is very strong on the total volatility of returns (see, for example, results for markets *C* and *E*). However, it creates large biases in the estimated variance decompositions (reported in Table 11) for the rest of the markets.

These results indicate that the auxiliary model containing empirical moments does not pick up certain characteristics of the data, namely, auto-correlation and time-varying volatility of returns, leading to large biases in AR and GARCH estimated parameters. The biases in estimated AR and GARCH parameters result in the misleading estimated variance decomposition of returns, especially when there is no strongly pronounced influence of one of the factors.

The results of the Monte Carlo using Indirect Inference are reported in Table 10. The parameter estimates for $j_i$ and $l_i$ are somewhat worse than their SMM counterparts. However, Indirect estimation results are obtained

after 300 Monte Carlo simulations only versus 500 simulations for SMM[2]. As for AR parameter $r$, its estimate is very close to the true value, which indicates that Indirect estimation using 'dual VAR' auxiliary model copes well with estimating the structural model containing AR processes. Efficient and consistent estimation of the model parameters results in the variance decomposition closely approximating the true contribution of latent factors in the total variance of returns. GARCH parameter estimates have the largest biases. However, normalizing the variance of the common factor to $1/(1-\rho^2)$ using the restriction (6) does not affect the variance decomposition results, reported in Table 11. Among GARCH coefficients the auto-regressive coefficient estimate is closer to its true value, which means that the auxiliary model picks up the autocorrelation of the residuals, while the autocorrelated variance of the residuals is not reflected in this model. This is an area for potential improvement in auxiliary modeling.

The results of the Monte Carlo experiment are consistent with the findings of Michaelides and Ng (2000), Andersen et al. (1999) and Gallant and Tauchen (1996). They show that although the conventional method of moments is the easiest to implement and the least computationally demanding, Indirect Inference estimator is superior to the conventional method of moments in terms of efficiency and consistency.

## 9. Discussion of the results of variance decompositions based on Indirect Inference estimated parameters

Monte Carlo experiment conducted in the above section demonstrates the superiority of the Indirect Inference estimation over SMM. Therefore, the discussion of the results is focused on the Indirect Inference results.

Figure 1 shows the variance decompositions for Thailand, Indonesia, Korea, Malaysia and Philippines over 2 periods – stability and crisis.

**Figure 1. Variance decompositions over the stable and crisis period based on Indirect Inference results.**



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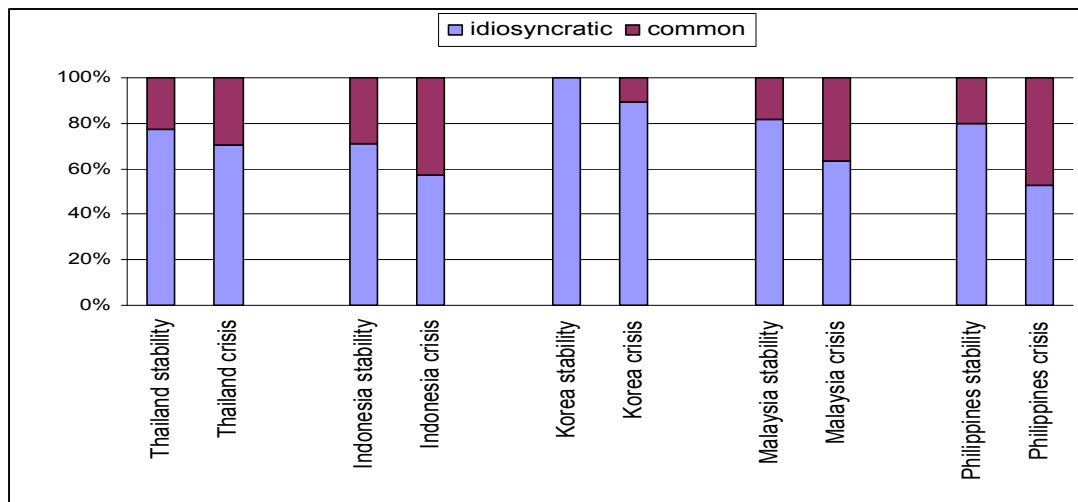
[2] In average Indirect estimations runs 10 times longer than SMM estimation for the same length of simulation path.

Figure 1 shows that before the crisis changes in the equity price index in all analyzed markets were driven by domestic (idiosyncratic) factors. In Korea the contribution of the domestic factors were almost 100%, while in other Asian emerging markets, the impact of idiosyncratic shocks ranges from 70 to 80%.

During the stability period common shocks attributed 23% to the total variance of Thailand equity price index (EPI) returns, 29% to the changes in the Indonesian EPI, 18% to the variance of Malaysian EPI returns, and 20% to the variance of Philippines EPI returns.

These results are consistent with the findings by Masih and Masih (1999), who conduct generalized variance decomposition analysis of 8 world stock markets, including Malaysia, and Thailand. They find that in Malaysian and Thai stock markets around a third of the variance of returns is explained by regional factors.

According to Indirect Inference results, all stock markets experienced an increase in common factor contribution to their total stock market volatility. Thailand experienced the smallest increase in the influence of common shocks, 7% of total variance of stock returns. This is followed by Korea with 10% increase, Indonesia with 14% increase, Malaysia with 18% and Philippines with 27%. Volatility of Korean equity market continued to be substantially dominated by idiosyncratic factors during the turbulent period .

Since contagion is represented by an increase in the common factor share in the total variance of returns, in a way it can be interpreted as increased correlation between emerging equity market returns during the crisis. The result that the change in the variance decomposition of Thailand's equity market returns is the smallest indicates that Thailand was a trigger in the Asian crisis, with the rest of the markets being affected by contagion from Thailand.

It is interesting to notice the difference between Korea and the rest of the emerging Asia. In Korean equity markets none of the volatility has been explained by the common shocks during the stable period, and even during the turbulent period only about 10% of the volatility is explained by common shocks. Whereas in Thailand, Indonesia, Malaysia and Philippines from 20 to 30% of the stock markets volatility is explained by common shocks. Taking into account that common shocks represent the forces that commonly affect all stock markets in the analyzed portfolio, these results support Krugman's (1998) argument that Korea has minor direct linkages with southeast Asia, and is structurally very different.

## 10. Latent Factor Extraction

Using the estimated parameters of the model (1) – (5) and observed time-series  of equity index returns allows us to extract the latent common and idiosyncratic factors applying a Kalman filter.

To extract the latent factors using the Kalman filter, first, the initial values of the factors and the initial value of the variance covariance matrix of the factors are chosen. Based on the initial values and the model describing the behavior of stock market returns, the next period stock market returns are predicted. Then the prediction error, which is a difference between actual and predicted values of stock returns, calculated. And the values of the

extracted factors and their variance-covariance matrix are corrected using the Kalman filter gain, which is the function of the prediction error. (Aoki (1987), Harvey (1990)). The corrected values are then used to predict the next period stock market returns, and so on.

Using the extracted factors and the estimated parameters of the model (1) – (6) the stock market returns are reconstructed. Reconstructed returns for 5 stock markets and actual returns are illustrated on charts 2 (a-j) for comparison. These charts demonstrate that the difference between reconstructed and actual returns is minimal or none, confirming that the 2 factor model with GARCH characteristics for common factor correctly describes the behavior of stock market returns.

Charts 3-7 demonstrate the shares of the common and idiosyncratic factors in total returns over the estimation periods of stability and crisis. The returns in these graphs are centered to zero (demeaned) and represented by the thin line. Common factors are represented by thick line. The difference between returns and common factor is the idiosyncratic factor. During the stability period all examined markets returns are dominated by idiosyncratic factor. The Korean equity market is an interesting case, where common factor had absolutely no impact on the returns during the stable period. We can see from the charts that during the turbulent period the influence of the common factor increases. It is especially clear in the case of the Philippines, Malaysia and Indonesia, where common factor impacts on the volatility of stock market returns increased by 14 to 27%.

## 11. Estimating the standard errors for factor contributions and test for shift-contagion

To assess the accuracy of the factor contribution estimates and to determine the statistical significance of the break in the relationship requires an accurate estimation of the standard errors for the factor contributions. However, the latent nature of the factors does not allow us to obtain the standard errors for the factor contribution estimates directly using the estimated standard errors of the parameters. In this situation we can turn to the residual bootstrapping technique that provides one way to address this problem.

There are several important assumptions that must be addressed with residuals bootstrapping. Unlike data bootstrapping, residual bootstrapping is very sensitive to the assumption that model (1) – (6) correctly describes the behavior of the stock market returns, and that the residuals of this model have an expected value of zero (Efron and Tibshirani, 1993). Addressing the first assumption, the Monte Carlo experiments and the comparison of the actual and fitted returns in the previous sections demonstrate that model (1) – (6) is correctly specified. The second assumption of the mean of the residuals being equal to zero also holds.

The idea behind bootstrapping the residuals is that we fix the parameters of model (1). Then we resample with replacement the residuals of model (1) and obtain the new sample of stock markets returns $s_b$ using the fixed parameters, extracted factors, and resampled residuals. Using the new sample $s_b$ idiosyncratic factor contributions $fc_{i,b}^C$ and common factor contributions $fc_{i,b}^W$ for $i=T, I, K, M, P$ and $b=1,..,B$ are estimated using the

Indirect Inference technique separately for the stable period and crisis period. The standard error of the factor $F$ contribution to the volatility of stock market $i$ for each period is then calculated as:

$$\hat{s}_i^F = \left( \sum_{b=1}^{B} \left( fc_{i,b}^F - \overline{fc}_i^F \right)^2 / (B-1) \right)^{\frac{1}{2}},$$

where:

$$\overline{fc}_i^F = \frac{1}{B} \sum_{b=1}^{B} fc_{i,b}^F$$

Efron and Tibshirani (1993) suggest that B = 200 bootstraps are enough to estimate the standard error.

Estimated standard errors can then be used to test the hypothesis of shift-contagion. Statistically significant differences between stable and crisis factor contributions will indicate the existence of shift contagion. The test-statistic is calculated as follows:

$$t = \frac{fc_{i,stable}^F - fc_{i,crisis}^F}{\hat{s}^F},$$

where $\hat{s}^F = \sqrt{(\hat{s}_{i,stable}^F)^2 + (\hat{s}_{i,crisis}^F)^2}$ is a pooled standard error, and

$T_{stable}$ and $T_{crisis}$ are the sample sizes of the stable and crisis period respectively.

Table 12 shows estimated common factor contributions for both stable and turbulent periods and their standard errors estimated using the bootstrapping technique. The last column in Table 12 shows the t-statistic of the test for contagion. Since the factor contributions are expressed as a percentage of total, standard errors for common factor and idiosyncratic factor contributions for particular markets are the same.

The results of the test for shift-contagion indicate that the hypothesis of no contagion is rejected at the 95% significance level. This confirms that the common factor played a significantly bigger role in the total volatility of stock market returns during the crisis period compared to the period of relative stability.

## 12. Conclusion

To investigate the nature of shift-contagion that possibly occurred during Asian financial crisis we use a latent factor model of stock returns to decompose the volatility of stock returns into two unobserved factors – idiosyncratic and common. However, the unobserved nature of the factors does not allow us to utilize simple econometric techniques to identify the parameters of the model and test for a structural shift between two periods- stability and crisis. Additionally, an investigation of the properties of the stock market returns data requires the imposition of a GARCH specification on the variance of the common factor.

To overcome these challenges the model is estimated using two simulation based techniques – namely, Indirect Inference and Simulated Method of Moments. The empirical results produced by the two methods differ substantially. Comparing SMM and Indirect Inference estimators using Monte Carlo experiment demonstrates that Indirect Inference produces more efficient, less biased estimates in the presence of heteroskedasticity. Since stock market return data exhibits strong auto-correlation and time-varying volatility, Indirect Inference is a better method of conducting variance decomposition analysis for stock market returns than conventional method of moments. Existing literature also establishes that Indirect Inference estimates have better small sample properties. Therefore we focus on the Indirect Inference results.

Based on the Indirect Inference results, volatility decomposition indicates that in core Asian emerging economies (Indonesia, Korea, Malaysia, Philippines and Thailand), common factors played a bigger role during the crisis that during the stability period. The smallest increase in common factor contribution occurred in Thailand, confirming previous findings that Thailand was a 'trigger' market in the Asian financial crisis. The significant increase of the common factor contribution to the volatility of all other Asian emerging markers indicates the occurrence of shift-contagion after the crisis started the Thai equity market.

Evidence of shift-contagion, or changes in cross-market linkages between stable and crisis periods, suggests that fund managers cannot only rely on historical estimates to measure portfolio risk. Country diversification is intended to mitigate overall portfolio risk to specific events or crisis. However, this research identifies that this diversification strategy can break down at precisely the time when it is needed. In so far as equity market volatility can affect the flow of capital in and out of country, and hence, affect domestic economic conditions, central bank and ministry of finance officials should take note that contagion effects from external sources can have material impacts on their domestic financial market conditions. By quantifying contagion effects, this research aims to highlight and access an important aspect of equity market risk to provide a ongoing step in improving financial market risk management.

**Table 1. Descriptive statistics of daily stock market returns over the stability and crisis period.**

| Stock Market | Stability period December 28, 1994 - March 31, 1997 | | | | | | Crisis period June 1, 1997 -August 31, 1998 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std.dev | Min | Max | Skewness | Kurtosis | Mean | Std.dev | Min | Max | Skewness | Kurtosis |
| Thailand | -0.1% | 1.1% | -4.4 | 4.2 | 0.09 | 1.47 | -0.4% | 3.1% | -7.8 | 17.2 | 1.34 | 3.94 |
| Indonesia | 0.1% | 0.9% | -4.0 | 3.3 | -0.23 | 3.09 | -0.4% | 4.5% | -18.6 | 20.7 | 0.13 | 3.95 |
| Korea | -0.1% | 1.4% | -4.4 | 3.8 | -0.03 | 1.01 | -0.1% | 4.7% | -11.8 | 22.5 | 0.72 | 2.96 |
| Malaysia | 0.1% | 0.7% | -3.1 | 5.0 | 0.54 | 4.98 | -0.5% | 2.9% | -9.4 | 13.7 | 0.94 | 3.48 |
| Philippines | 0.0% | 0.8% | -2.7 | 2.4 | -0.03 | 1.22 | -0.4% | 2.2% | -6.4 | 11.1 | 0.45 | 2.62 |

**Chart 1. (a) Thailand stock market returns.**
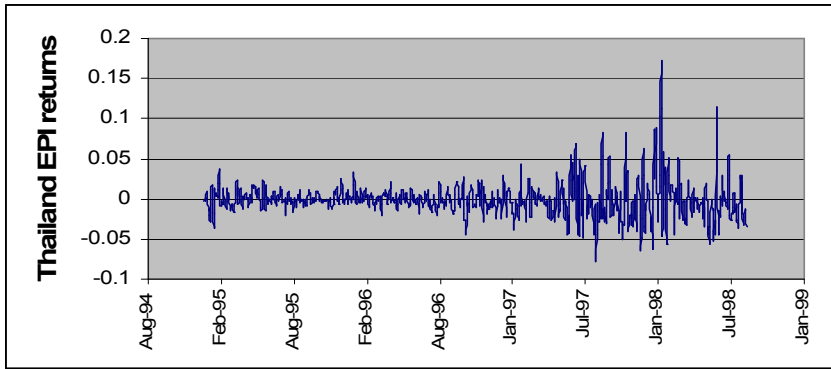
**(b) Indonesian stock market returns.**
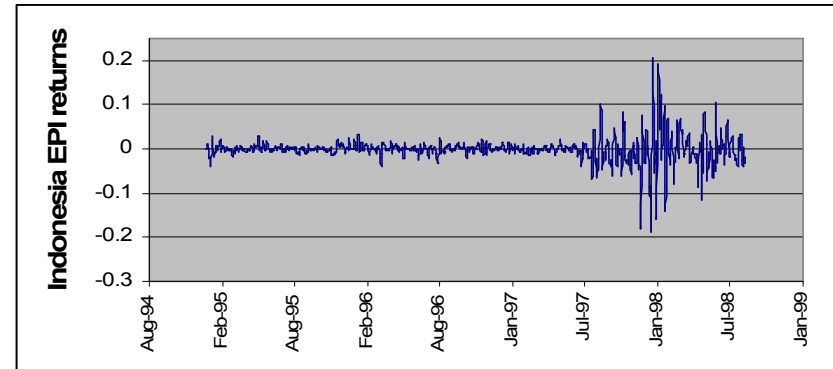
**(c) Malaysian stock market returns.**
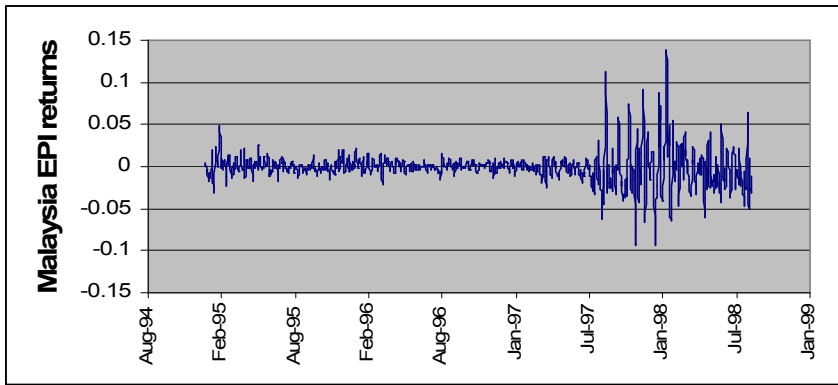
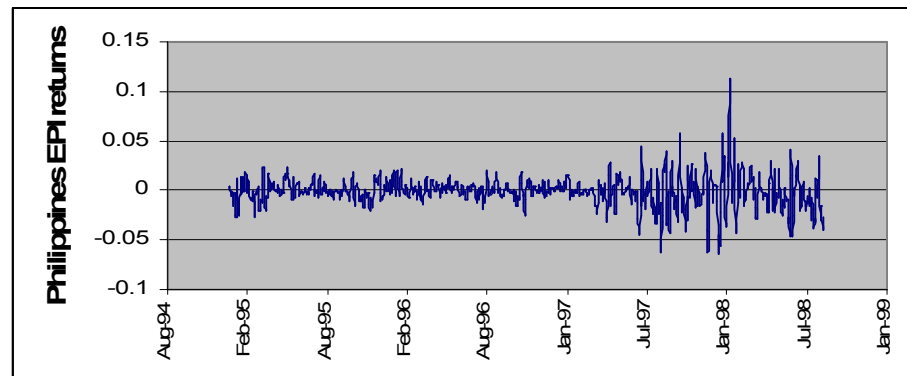**(d) Korean stock market returns.**
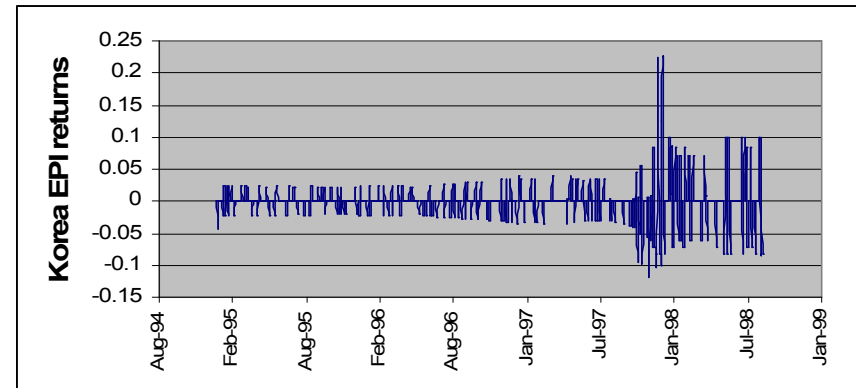
**(e) Philippines stock market returns**



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**Table 2. GARCH(p, q) specification selection – results of the stability period maximum likelihood estimation.**

| | ARCH(1) | | GARCH(1,1) | | GARCH(1,2) | | GARCH(2,1) | | GARCH(2,2) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | AIC | BIC | AIC | BIC | AIC | BIC | AIC | BIC | AIC | BIC |
| Thailand | -725.8 | -732.4 | -701.0 | -709.7 | -694.6 | -705.5 | -701.6 | -712.6 | -695.2 | -708.3 |
| Indonesia | -581.5 | -588.0 | -554.5 | -563.3 | -553.5 | -564.5 | -553.7 | -564.6 | -553.9 | -567.0 |
| Korea | -978.3 | -984.8 | -970.1 | -978.4 | -967.6 | -978.5 | -970.2 | -981.1 | -968.7 | -981.8 |
| Malaysia | -518.1 | -524.7 | -480.0 | -488.8 | -480.3 | -491.3 | -483.2 | -492.1 | -478.7 | -491.7 |
| Philippines | -511.7 | -518.2 | -495.2 | -503.9 | -493.5 | -504.4 | -494.8 | -505.7 | -494.4 | -507.5 |

**Table 3. Maximum likelihood parameter estimates of univariate GARCH(1,1) models for stock market returns over the stability period 1/1/95 – 31/3/97 and crisis period 1/6/97 – 31/8/98. t-ratios are in brackets.**

| Parameter | Thailand | | Indonesia | | Korea | | Malaysia | | Philippines | |
|---|---|---|---|---|---|---|---|---|---|---|
| | stable | crisis | stable | crisis | stable | crisis | stable | crisis | stable | crisis |
| $\rho_0$ | -0.015 (-0.49) | -0.325 (-2.58) | 0.022 (0.96) | -0.149 (-1.20) | -0.054 (-1.08) | -0.242 (-1.45) | 0.018 (0.90) | -0.318 (-2.93) | 0.011 (0.52) | -0.171 (-2.43) |
| $\rho_1$ | 0.593 (16.41) | 0.546 (10.62) | 0.606 (16.38) | 0.565 (11.39) | 0.382 (9.30) | 0.327 (5.79) | 0.545 (15.09) | 0.507 (9.47) | 0.646 (18.78) | 0.642 (12.88) |
| $\alpha_0$ | 0.035 (1.52) | 1.432 (3.07) | 0.121 (4.94) | 0.471 (2.31) | 0.731 (3.63) | 0.204 (1.36) | 0.007 (2.33) | 0.969 (2.16) | 0.023 (2.88) | 0.224 (2.64) |
| $\alpha_1$ | 0.089 (2.07) | 0.348 (3.45) | 0.395 (4.70) | 0.330 (4.52) | 0.181 (3.62) | 0.113 (5.38) | 0.095 (3.48) | 0.657 (4.03) | 0.192 (4.57) | 0.427 (4.31) |
| $\beta_1$ | 0.851 (11.67) | 0.461 (4.08) | 0.375 (4.46) | 0.693 (13.08) | 0.382 (2.55) | 0.887 (42.24) | 0.886 (30.55) | 0.360 (2.71) | 0.756 (16.43) | 0.572 (8.17) |
| Log-likelihood value | -697.04 | -738.56 | -550.53 | -813.96 | -966.13 | -887.94 | -476.05 | -710.97 | -491.15 | -598.24 |

**Table 4. SMM parameter estimates and their asymptotic standard errors (H=50).**

| Parameter | Stability | | Crisis | |
|---|---|---|---|---|
| | Parameter estimate | Std. dev. | Parameter estimate | Std. dev. |
| $\varphi_T$ | 1.09 | 0.098 | 2.85 | 0.285 |
| $\varphi_I$ | 0.85 | 0.045 | 4.24 | 0.539 |
| $\varphi_K$ | 2.07 | 0.105 | 6.81 | 0.545 |
| $\varphi_M$ | 0.69 | 0.037 | 2.38 | 0.624 |
| $\varphi_P$ | 0.78 | 0.040 | 1.93 | 0.136 |
| $\lambda_T$ | 0.72 | 49.47 | 2.53 | 569.06 |
| $\lambda_I$ | 0.71 | 49.5 | 4.06 | 932.95 |
| $\lambda_K$ | -0.14 | 6.82 | 1.70 | 384.21 |
| $\lambda_M$ | 0.63 | 45.09 | 2.46 | 536.53 |
| $\lambda_P$ | 0.60 | 42.22 | 1.91 | 435.34 |
| $\rho$ | 0.05 | 503.31 | 0.12 | 3970.8 |
| $\alpha$ | 0.68 | 737.20 | 0.18 | 570.87 |
| $\beta$ | 0.18 | 230.80 | 0.68 | 3671.3 |

**Table 5. SMM results: Variance decompositions expressed as a percentage of total over the stability and crisis periods (H=50).**

| Market | Stability | | Crisis | |
|---|---|---|---|---|
| | Idiosyncratic component | Common component | Idiosyncratic component | Common component |
| Thailand | 69.5 | 30.5 | 55.6 | 44.4 |
| Indonesia | 58.7 | 41.3 | 51.8 | 48.2 |
| Korea | 99.5 | 0.5 | 94.0 | 6.0 |
| Malaysia | 55.1 | 44.9 | 48.0 | 52.0 |
| Philippines | 62.5 | 37.5 | 50.3 | 49.7 |

**Table 6. GMM results: Variance decompositions expressed as a percentage of total over the stability and crisis periods.**

| Market | Stability | | Crisis | |
|---|---|---|---|---|
| | Idiosyncratic component | Common component | Idiosyncratic component | Common component |
| Thailand | 69.7 | 30.3 | 62.4 | 37.6 |
| Indonesia | 60.3 | 39.7 | 48.9 | 51.1 |
| Korea | 99.9 | 0.1 | 94.3 | 5.7 |
| Malaysia | 52.5 | 47.5 | 40.0 | 60.0 |
| Philippines | 62.7 | 37.3 | 55.9 | 44.1 |

**Table 7. Indirect inference parameter estimates and their standard errors (H=50).**

| Parameter | Stability | | Crisis | |
|---|---|---|---|---|
| | Parameter estimate | Std.dev. | Parameter estimate | Std.dev. |
| $\varphi_T$ | 0.99 | 0.30 | 2.84 | 0.56 |
| $\varphi_I$ | -0.72 | 0.23 | -3.04 | 1.13 |
| $\varphi_K$ | 1.73 | 0.40 | 4.71 | 1.64 |
| $\varphi_M$ | -0.62 | 0.18 | 2.16 | 0.47 |
| $\varphi_P$ | 0.63 | 0.17 | 1.57 | 0.39 |
| $\lambda_T$ | 0.43 | 0.44 | 1.61 | 1.62 |
| $\lambda_I$ | 0.36 | 0.40 | 2.28 | 2.06 |
| $\lambda_K$ | 0.002 | 0.42 | 1.38 | 1.77 |
| $\lambda_M$ | 0.23 | 0.30 | 1.40 | 1.33 |
| $\lambda_P$ | 0.25 | 0.31 | 1.28 | 0.96 |
| $\rho$ | 0.61 | 0.55 | 0.51 | 0.33 |
| $\alpha$ | 0.63 | 5.94 | 0.16 | 1.77 |
| $\beta$ | 0.07 | 15.22 | 0.77 | 3.01 |

**Table 8. Indirect Inference results: Variance decompositions expressed as a percentage of total over the stability and crisis periods (H=50).**

| Market | Stability 1/1/95 – 31/3/97 | | Crisis 1/6/97 – 31/8/98 | |
|---|---|---|---|---|
| | Idiosyncratic component | Common component | Idiosyncratic component | Common component |
| Thailand | 77.2 | 22.8 | 70.3 | 29.7 |
| Indonesia | 70.9 | 29.1 | 57.3 | 42.7 |
| Korea | 100.0 | 0.0 | 89.6 | 10.4 |
| Malaysia | 81.6 | 18.4 | 63.8 | 36.2 |
| Philippines | 79.7 | 20.3 | 53.0 | 47.0 |

**Table 9. Monte Carlo estimation results for SMM.**

T = 300, N=500, standard errors are in brackets

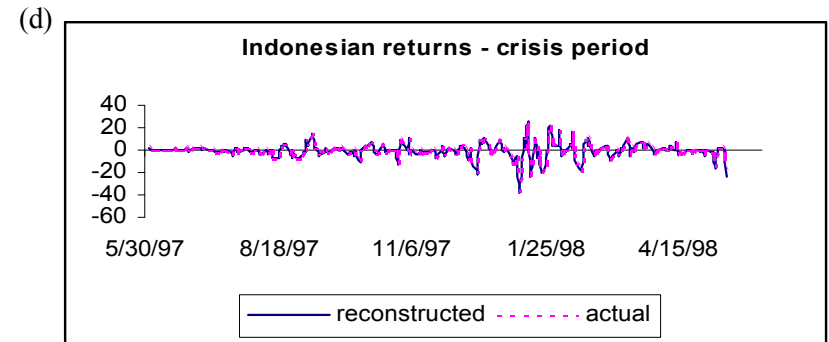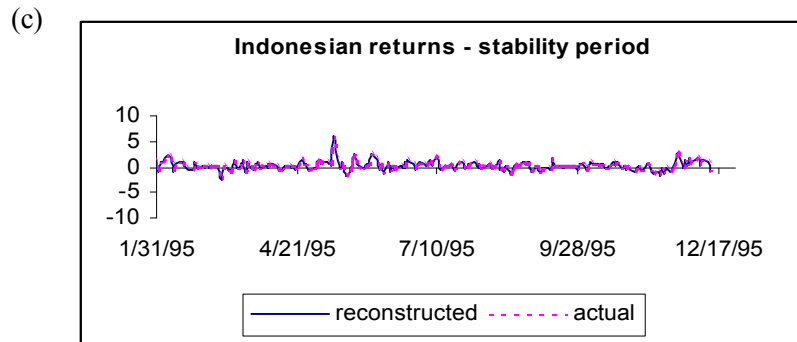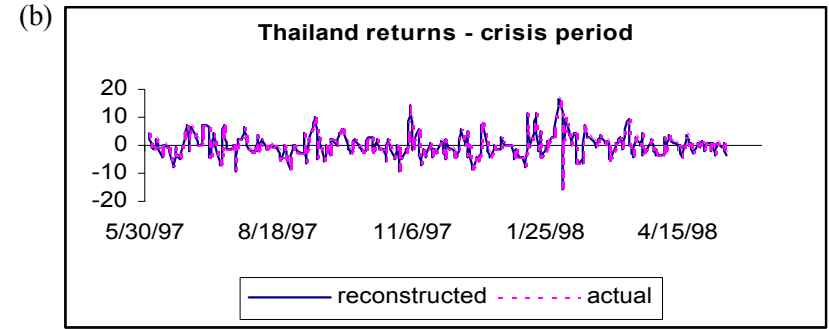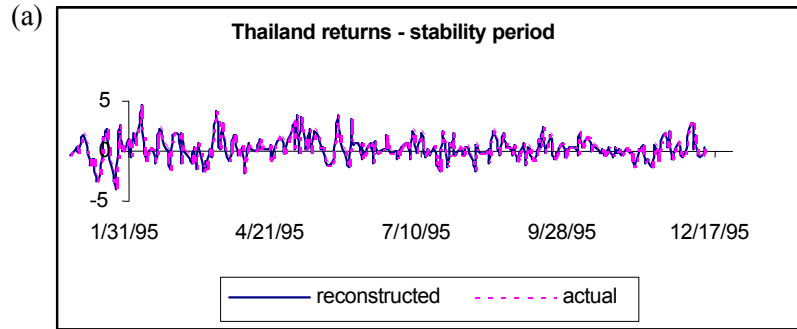| Parameters | True values | Estimated values | | |
|---|---|---|---|---|
| | | H=20 | H=50 | H=100 |
| $\varphi_a$ | 0.70 | 0.69 (0.031) | 0.69 (0.029) | 0.69 (0.029) |
| $\varphi_b$ | 0.50 | 0.49 (0.030) | 0.49 (0.029) | 0.49 (0.029) |
| $\varphi_c$ | 1.00 | 0.98 (0.042) | 0.98 (0.041) | 0.98 (0.041) |
| $\varphi_d$ | 1.50 | 1.47 (0.064) | 1.47 (0.062) | 1.48 (0.062) |
| $\varphi_e$ | 0.60 | 0.59 (0.072) | 0.59 (0.072) | 0.59 (0.073) |
| $\lambda_a$ | 0.50 | 0.55 (13.51) | 0.54 (54.20) | 0.54 (55.00) |
| $\lambda_b$ | 1.00 | 1.11 (26.90) | 1.08 (108.4) | 1.08 (102.4) |
| $\lambda_c$ | 0.20 | 0.22 (5.73) | 0.21 (21.82) | 0.20 (20.80) |
| $\lambda_d$ | 1.10 | 1.22 (29.69) | 1.18 (119.2) | 1.20 (119.2) |
| $\lambda_e$ | 2.00 | 2.22 (53.76) | 2.16 (217.0) | 2.14 (217.0) |
| $\rho$ | 0.50 | 0.21 (108.04) | 0.31 (272.5) | 0.30 (272.5) |
| $\alpha$ | 0.30 | 0.15 (430.57) | 0.15 (528.3) | 0.17 (510.0) |
| $\beta$ | 0.30 | 0.40 (147.27) | 0.86 (340.4) | 0.70 (321.4) |

**Table 10. Monte Carlo estimation results for Indirect Inference.**

**T=300, N=200. Standard errors are in brackets.**

| Parameters | True values | Estimated values | | |
|---|---|---|---|---|
| | | H=20 | H=50 | H=100 |
| $\varphi_a$ | 0.70 | 0.66 (0.044) | 0.66 (0.043) | 0.65 (0.044) |
| $\varphi_b$ | 0.50 | 0.45 (0.046) | 0.45 (0.045 ) | 0.45 (0.045) |
| $\varphi_c$ | 1.00 | 0.88 (0.059) | 0.90 (0.058) | 0.89 (0.058) |
| $\varphi_d$ | 1.50 | 1.34 (0.095) | 1.34 (0.095) | 1.34 (0.093) |
| $\varphi_e$ | 0.60 | 0.52 (0.124) | 0.52 (0.138) | 0.53 (0.148) |
| $\lambda_a$ | 0.50 | 0.39 (0.074) | 0.40 (0.070) | 0.38 (0.070) |
| $\lambda_b$ | 1.00 | 0.76 (0.098) | 0.76 (0.097) | 0.75 (0.093) |
| $\lambda_c$ | 0.20 | 0.18 (0.090) | 0.18 (0.090) | 0.18 (0.085) |
| $\lambda_d$ | 1.10 | 0.83 (0.163) | 0.84 (0.160) | 0.83 (0.154) |
| $\lambda_e$ | 2.00 | 1.55 (0.194) | 1.55 (0.201) | 1.56 (0.189) |
| $\rho$ | 0.50 | 0.54 (0.108) | 0.53 (0.107) | 0.54 (0.105) |
| $\alpha$ | 0.30 | 0.40 (0.200) | 0.39 (0.240) | 0.38 (0.256) |
| $\beta$ | 0.30 | 0.79 (103062) | 0.87 (99E+3) | 0.76 (105269) |

**Table 11. Monte Carlo variance decompositions as a percentage of total.**

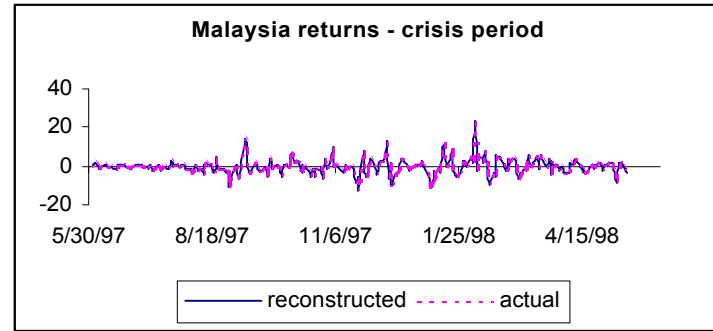| Market | Using True Parameters | | Using SMM estimated parameters | | Using Indirect Inference estimated parameters | |
|---|---|---|---|---|---|---|
| | $\dfrac{f_i^2}{f_i^2 + l_i^2/(1-r^2)}$ | $\dfrac{l_i^2/(1-r^2)}{f_i^2 + l_i^2/(1-r^2)}$ | $\dfrac{\hat{f}_i^2}{\hat{f}_i^2 + \hat{l}_i^2/(1-\hat{r}^2)}$ | $\dfrac{\hat{l}_i^2/(1-\hat{r}^2)}{\hat{f}_i^2 + \hat{l}_i^2/(1-\hat{r}^2)}$ | $\dfrac{\tilde{f}_i^2}{\tilde{f}_i^2 + \tilde{l}_i^2/(1-\tilde{r}^2)}$ | $\dfrac{\tilde{l}_i^2/(1-\tilde{r}^2)}{\tilde{f}_i^2 + \tilde{l}_i^2/(1-\tilde{r}^2)}$ |
| A | 66.2 | 33.8 | 54.2 | 45.8 | 67.1 | 32.9 |
| B | 20.0 | 80.0 | 11.8 | 88.2 | 21.2 | 78.8 |
| C | 96.2 | 3.8 | 94.1 | 5.9 | 95.7 | 4.3 |
| D | 65.0 | 35.0 | 58.1 | 41.9 | 67.5 | 32.5 |
| E | 8.3 | 91.7 | 7.5 | 92.5 | 8.2 | 91.8 |

**Chart 2 (a-j). Actual and reconstructed equity market returns for Thailand, Indonesia, Korea, Malaysia, Philippines during the periods of stability and crisis.**
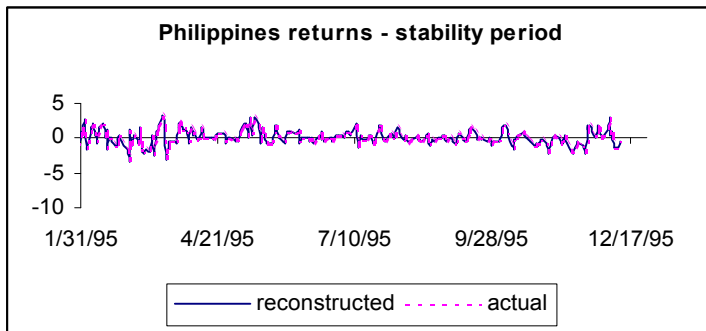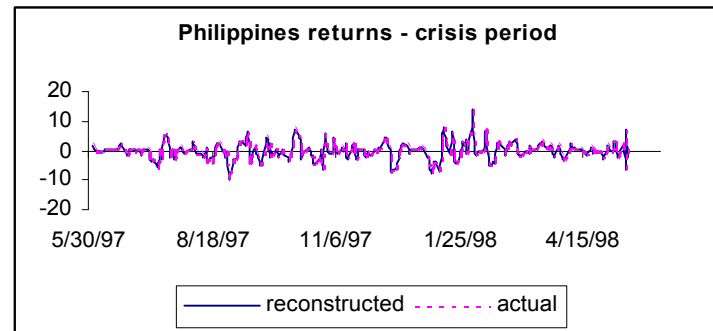
(a)



Thailand returns - stability period
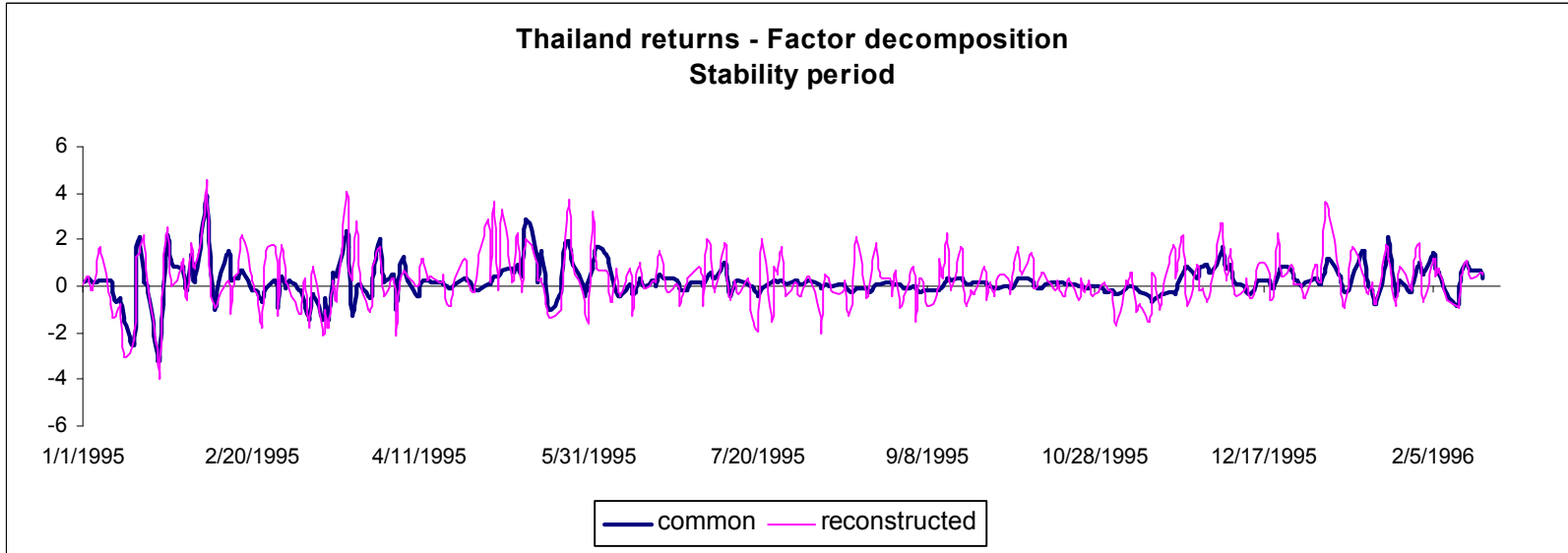
reconstructed          actual

(b)



Thailand returns - crisis period

reconstructed          actual

(c)



Indonesian returns - stability period

reconstructed          actual

(d)



Indonesian returns - crisis period

reconstructed          actual

(e)



Korean returns - stability period

reconstructed          actual

(f)



Korean returns - crisis period

reconstructed          actual

28

(g)

**Malaysian returns - stability period**



(h)

**Malaysia returns - crisis period**



(i)

**Philippines returns - stability period**



(j)

**Philippines returns - crisis period**



29

Chart 3 (a)



Chart 3 (b)

Chart 4 (a)



**Indonesian returns - Factor decomposition**
**Stability period**

common    reconstructed

Chart 4 (b)



**Indonesian returns - Factor decomposition**
**Crisis period**

common    reconstructed
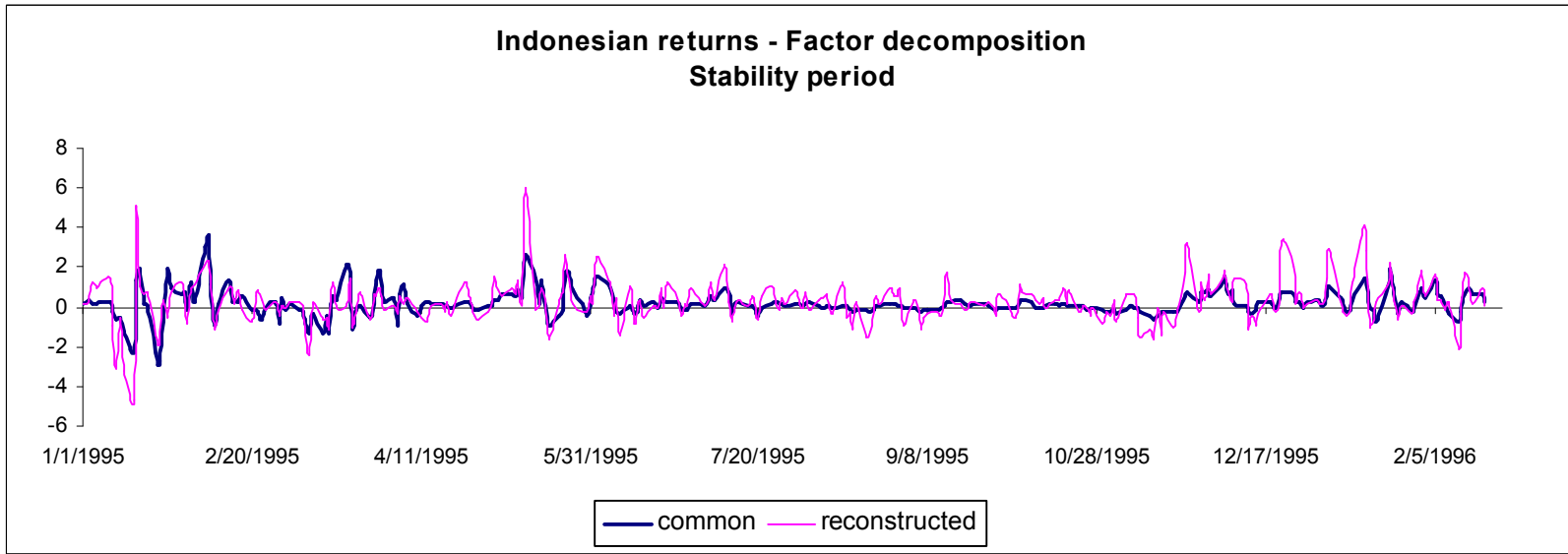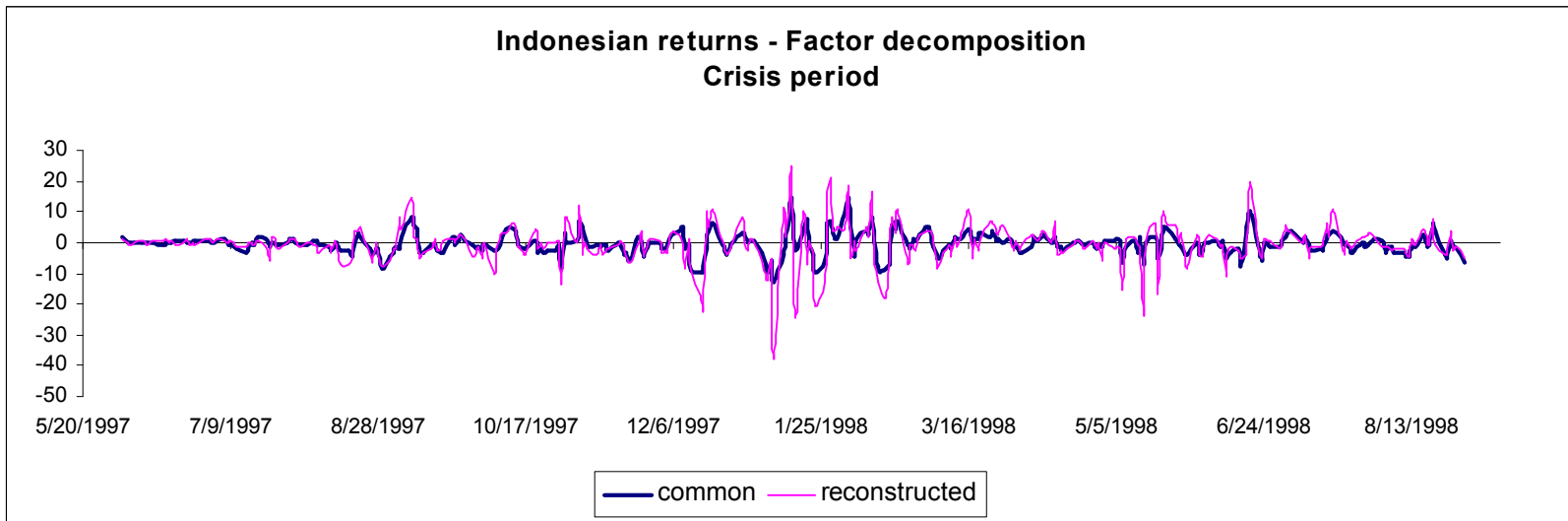
Chart 5 (a)



Chart 5 (b)

Chart 6 (a)



**Malaysian returns - Factor decomposition
Stability period**

common ——— reconstructed

Chart 6 (b)



**Malaysian returns - Factor decomposition
Crisis period**

common ——— reconstructed
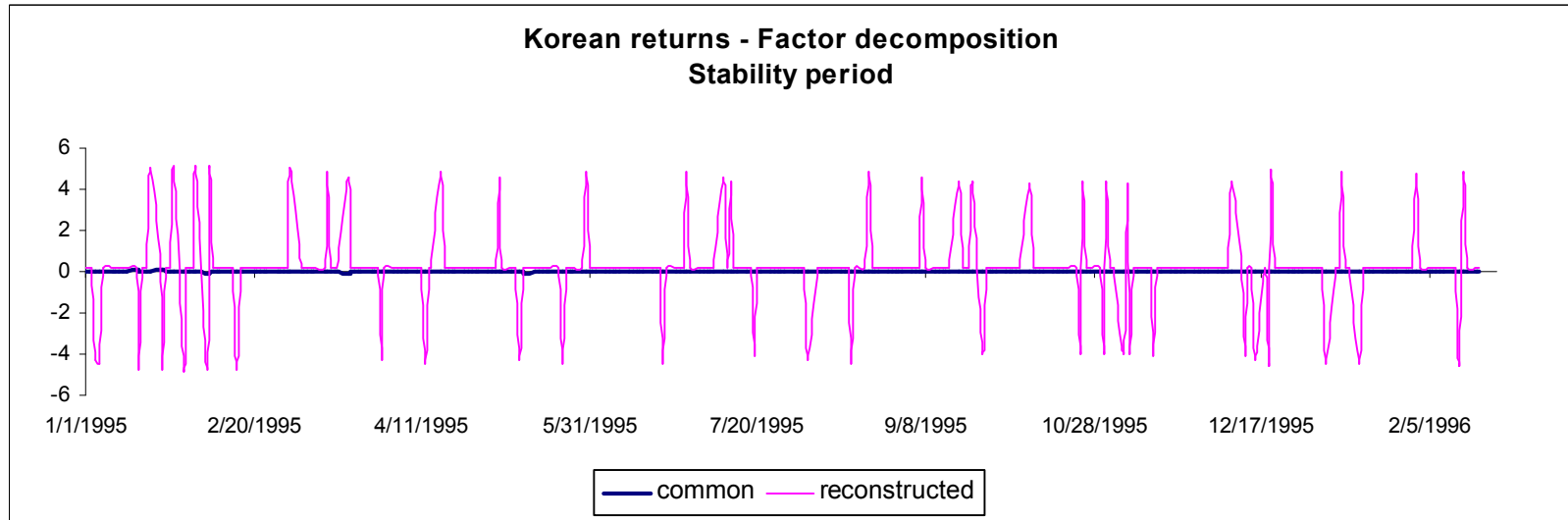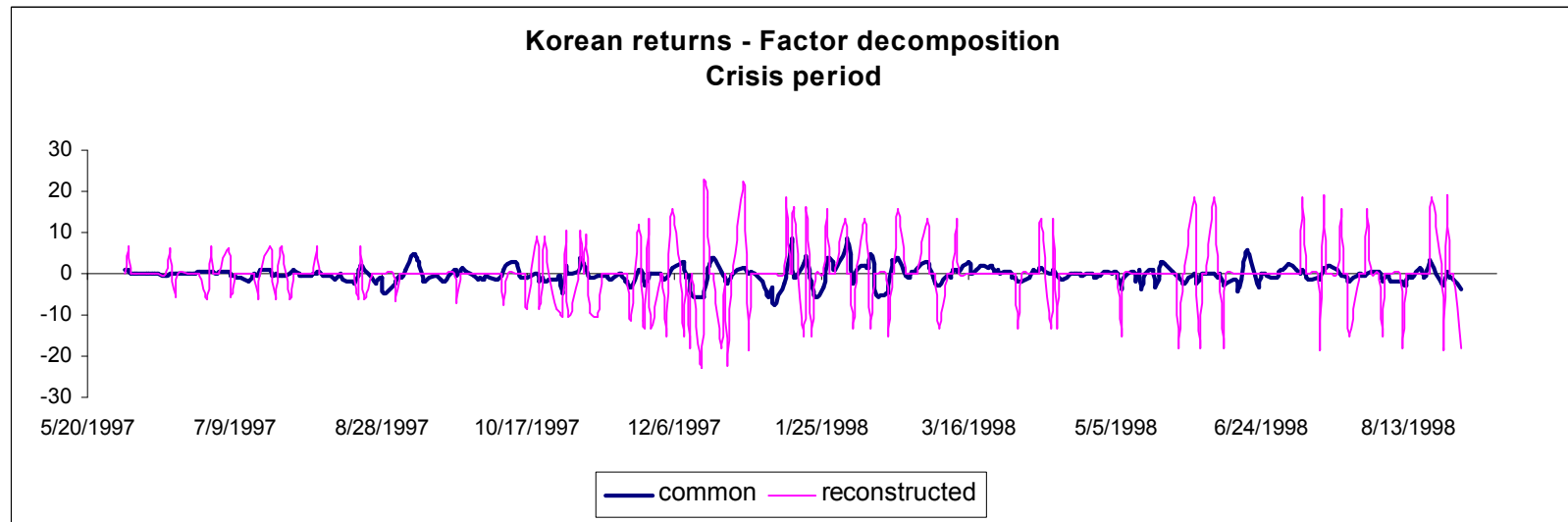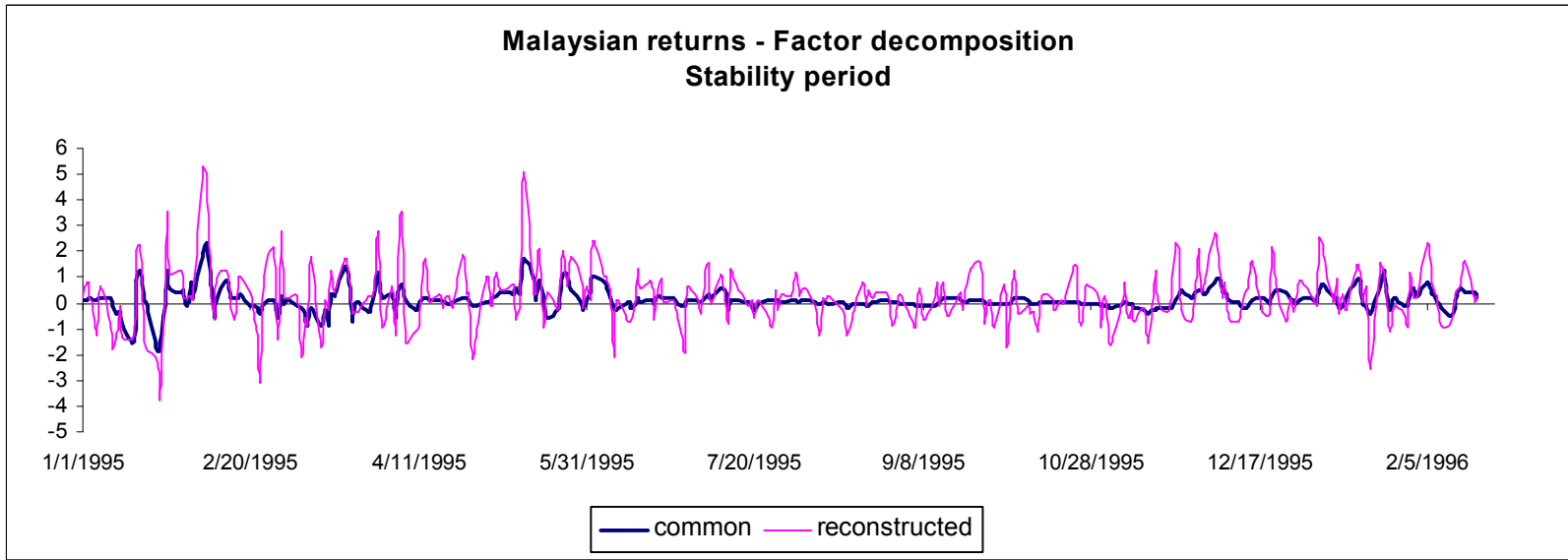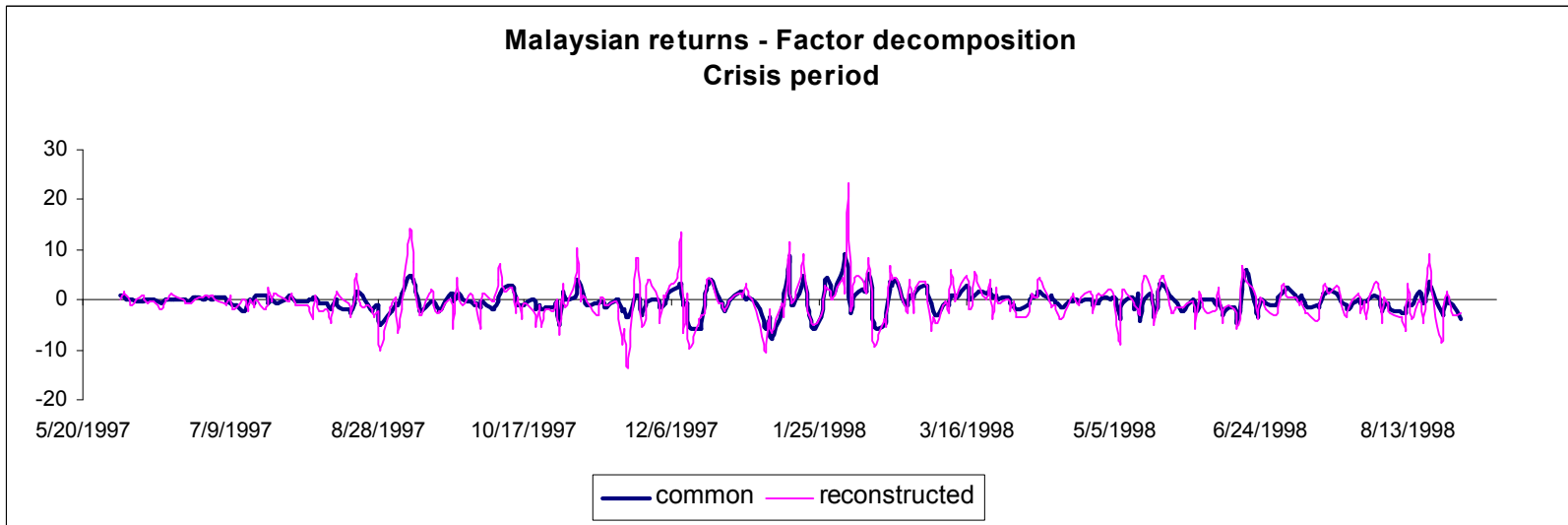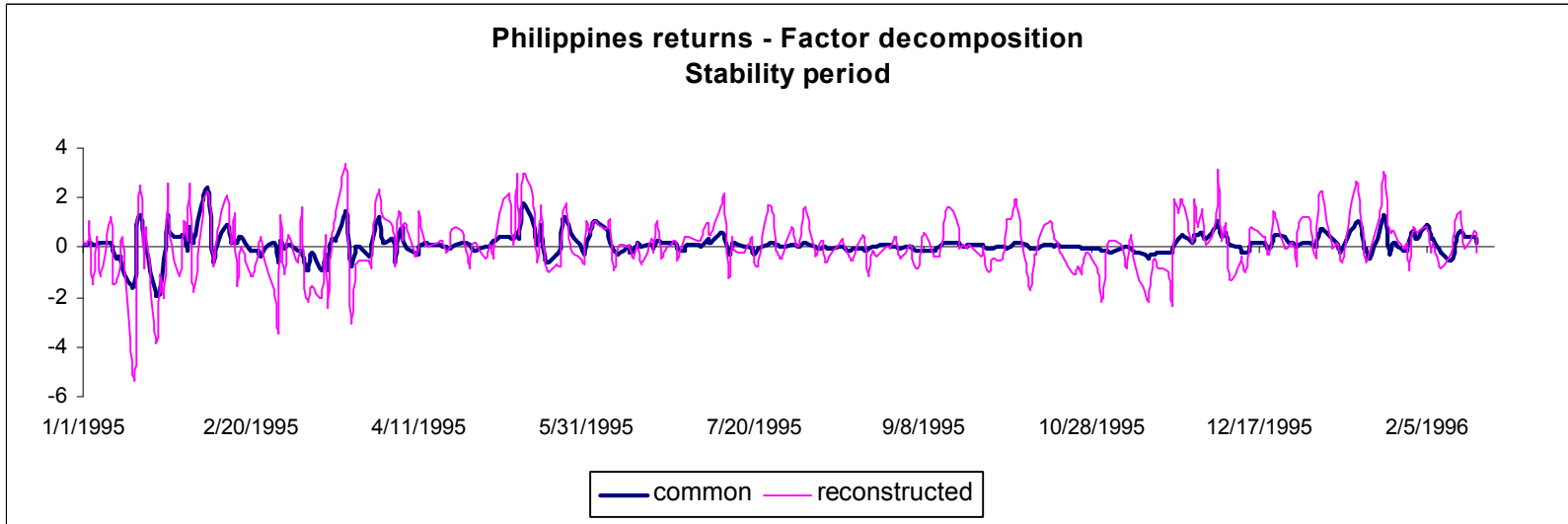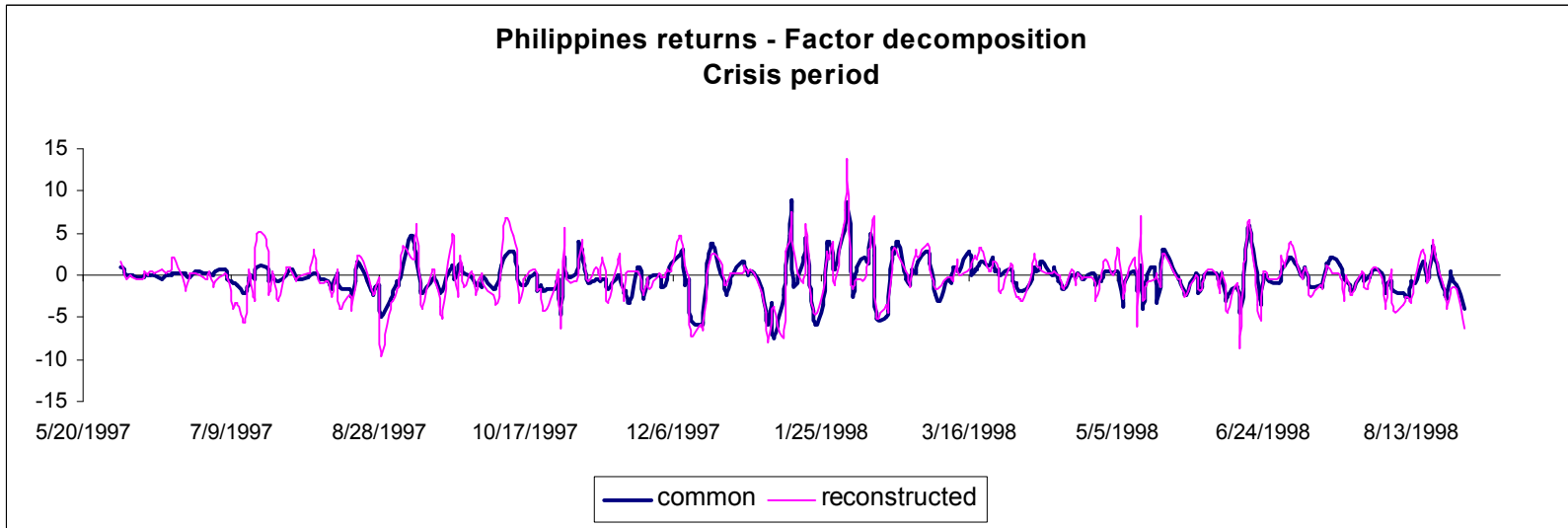
Chart 7 (a)



Chart 7 (b)

**Table 12. Test for contagion using Indirect Inference results. Common factor contributions and their standard errors over the stability and crisis periods**

| Market | Stability (587 obs) 1/1/95 – 31/3/97 | | Crisis (326 obs) 1/6/97 – 31/8/98 | | Test for shift-contagion |
|---|---|---|---|---|---|
| | Common component | Standard error | Common component | Standard error | t-statistic |
| Thailand | 22.8 | 2.45 | 29.7 | 2.20 | 2.10* |
| Indonesia | 29.1 | 2.41 | 42.7 | 2.33 | 4.06* |
| Korea | 0.0 | 0.03 | 10.4 | 1.20 | 8.66* |
| Malaysia | 18.4 | 2.22 | 36.2 | 2.40 | 5.44* |
| Philippines | 20.3 | 2.48 | 47.0 | 2.59 | 7.45* |

* - hypothesis of shift-contagion cannot be rejected at 95% level of significance.

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