JOURNAL OF ECONOMIC DEVELOPMENT 1
Volume 39, Number 2, June 2014

BANK STOCK VOLATILITY AND CONTAGION: AN EMPIRICAL INVESTIGATION WITH APPLICATION OF MULTIVARIATE GARCH MODELS

WIDED BEN MOUSSA*

Universiité Paris-Ouest Nanterre, France

This paper uses a multivariate GARCH modelling to describe the relationship between the systemic risk and the stock return in the banking industry in Thailand, Malaysia, Korea, Indonesia and Philippines. The banking industry comprises the large banks and the small-medium size banks.

The advantage of this approach is the incorporation of time-variation in volatility consistent with empirical observations about the behaviour of stock return. Second the factor approach is adopted to incorporate intra-industry contagion within the banking sector. This so-called industry effect is designed to capture intra-industry information spillover between the large and the small-medium banks. Finally, the study provides evidence on these relations before and after the Asian financial crises of 1997, thereby implicitly testing for the impact of structural break.

Keywords: Systematic Risk, Contagion, Bivariate-GARCH Model
JEL classification: G01, G02, G21, G32, G33

1. INTRODUCTION

The understanding of risk has continued to increase in the banking industry, which has a feature of high financial leverage. Banks have played an important role as liquidity providers in many financial markets. When a bank suffers operational problems of failures, it could easily adversely affect the whole economy.

During the 1990's, emerging countries such as Asian countries experienced various restructuring in their banking sector; the banking sector has changed with a rapid increase of the number of banks, which led to an over-banking situation. Also the trends toward conglomeration and globalization have accelerated over the last decade. These trends helped by major technological innovations and regulatory changes have led to

* The author would like to thank an anonymous referee for very useful comments and suggestions.

increasing the occurrence of mergers and acquisitions of a great number of banks; consequently the sector becomes more concentrated, and an increasing dominance of large banks appears. These trends have also attracted serious scrutiny from regulators and researchers because the sheer size of these “mega” firms has led to greater concerns over heightened market power, increased systemic risk, stronger moral hazard incentives, and the rising costs of the “too-big-to-fail” doctrine.

Thus, it is important to examine the following questions:

(1) Are the risks and returns of large banks and small banks for each country, tightly linked?
(2) Does the bank size affect the magnitudes of these risk-return linkages?
(3) Has a period of turbulence which occurred in the same time of the anticipation of financial crisis, significantly affected bank risk and return patterns?

In this note, we use a multivariate GARCH model to investigate the intra-industry transmission of changes in the level and volatility of stock returns. While there have been numerous studies of intra-market interdependence and the more extreme case of contagion, this so called industry effect is designed to capture intra-industry information spillover between the large and the small banks.

Our analysis is to focus on return and risk linkages across the banking sector. Our estimation is carried out for large and small banks in order to determine how the linkage differs between the large firms and their smaller counterparts, and how consolidation in these industries can alter the spillover patterns. The strength of the interdependence, or the spillover effect, can also help to determine the intensity of competition between the two groups of banks with stronger spillover effects indicating more intense competition. Lastly, we examine the effects of the 1997 turbulence on the risk and return levels of large and small banks in our sample.

The empirics are conducted on a sample of banks from five Asian markets. The five markets of Indonesia, Korea, Malaysia, the Philippines and Thailand are chosen because of their close association with each other in economic, political and cultural terms. The daily time-series covers the period from 1994:12:30 to 1997:12:31, which includes the 1997 Asian financial crisis. It provides a large sample of 784 observations.

Our main findings are that large banks exhibit less volatility spillover than their smaller counterparts, while the converse is true for spillover of stock returns. These results provide evidence in favour of the industry effect with a view of the larger banks as market leaders.

Our contagion’s analysis which is defined as an excess of the spillover effect observed on turbulent period, shows that contagion spillover exists within the banking sector in each market leading to a positive intra-industry effect, but the strength of this relation is likely to be unidirectional from large to small banks.

The remainder of this note is organized as follows: the next section reviews the literature related bank failures and contagion: the first sub-section outlines literature review about return and volatility spillover/contagion effect with empirical methodology, and the second sub-section reveals the impact of the size in the failure, section 3 contains a description of data and methodology, section 4 discusses the empirical results, and the end contains concluding remarks.

2. LITERATURE REVIEW

2.1. Theoretical and Empirical Debate

Kaufman (1994) defines contagion as “a term used to describe the spillover of the effects of shocks from one or more firms to others”. Contagion is thought to be both more likely to occur and more serious in banking than in other industries. According to Kaufman, “bank contagion is hypothesized to: (1) occur faster, (2) spread more broadly within the industry, (3) result in a larger number of failures, (4) result in larger losses to creditors (depositors), and (5) spread more beyond the banking industry and cause substantial damage to the financial system as a whole and the macroeconomy”.

Contagion effect means when a company announces that it is filing bankruptcy, investors are unable to differentiate the operational or financial situations of others within the same industry. This phenomenon is considered more problematic in the banking sector than in other industries because of the perceived greater speed arising from runs, the larger losses to creditors arising from the high degree of leverage in the sector, and the potential wider impact on the economy through the spread of loss into other financial sectors.

The finance literature provides several approaches to model and forecast volatility in financial markets. The most popular are the GARCH models proposed by Bollerslev (1986) which are a generalized version of the auto regressive conditional heteroskedasticity models (ARCH models), introduced by Engle (1982). They present the advantage of incorporating the time-varying properties of volatility.

Elyasiani and Mansur (2003) utilise a bivariate GARCH methodology to determine the return interdependence and volatility transmission among the major US, German, and Japanese banks. A multivariate GARCH methodology is also used by Elyasiani, Mansur and Pagano (2007) to analyze the linkages for large and small firms. They find that a multivariate GARCH model can adequately account for time-variation in the risk and return patterns and the inter-industry transmission of shocks among three industries (commercial banks, securities firms, and life insurance companies).

Lin, Penm, Wu and Chiu (2004) utilise GARCH(1,1)-M models to test stock returns of China, Hong Kong and Taiwan’s banking industries for volatility clustering phenomenon, and explores the effect stock returns of large banks and small-medium size banks from the three regions have upon each other. They then contrast the industry contagion effect in the banking industry before and after the Asian financial crisis.

Neuberger (1994) employs a GARCH model to estimate factor volatilities as determinants of risk premia. He estimates a five-factor model of individual bank holding company stock returns, where the factors are proxied by sub-sample portfolios of assets as well as excess returns on market and interest rates. The Neuberger's paper is based on the econometric model put forward by Engle *et al*. (1990b) and allows for a system estimation of returns on a number of assets. He finds evidence in favour of equity market contagion pervading bank stocks.

Another set of papers examines contagion of financial markets by testing for higher correlation between markets during crisis times (King and Wadhwani, 1990; Forbes and Rigobon, 2002).

King and Wadhwani (1990) were the first to measure contagion as a significant increase in the correlation between asset returns. Specifically, they analyzed the correlation US, UK and Japanese equities return around the time of the 1987 stock market crash and found that the degree of correlation had increased after October 1987.

Forbes and Rigonbon (2002) distinguish between contagion and interdependence as follows: "it is only contagion if cross-market co-movement increases significantly after the shock". Otherwise, a continued high level of market correlation suggests the prevalence of strong linkages between the two economies in all states of the world.

Bekaert *et al*. (2003) adopt this same approach and describe contagion as the "correlation [between markets or firms] over and above what one would expect from economic fundamentals".

Favero and Giavazzi (2002) use a two-step approach to measure contagion: first they identify the channel of the transmission estimating of model of interdependence and second, they check whether the strength of the transmission channel has changed significantly following a crisis.

2.2. Does the Size of the Financial Institution Matter?

The particular characteristics of the banking industry in the context of the role and importance of risk have been previously acknowledged. The banking sector has a high degree of financial leverage which is a feature that has meant that the sector is typically excluded from traditional studies. That is, leverage ratios in the banking sector are regarded as extreme when compared to other industrial and manufacturing sectors. Further, the nature of banks as financial intermediaries means that when banks suffer operational problems or failures, the resultant impact can easily have an adverse effect on the entire economy. Through various domestic regulations and international standards, such as the versions of Basle, there is now a strong focus on risk management systems in banks and volatility dampening through formal models, such as Value-at-Risk. Since the nineteenth century, researchers have acknowledged that a bank which experiences operational difficulties will have various impacts on other financial institutions. Each bank has the following types of contracts: (1) payment systems; (2) the interbank market; and (3) the market for credit and risk management instruments (such as derivatives). The interbank relationships both in a formal sense and through an internal market have resulted in the transmission of risk among banks both domestically and internationally. For instance, the recent savings and loans 'crisis' in the USA, along with the 1990s crises in Mexico, Asia and Russia, all demonstrate the potential influence of transmission of risk within the banking industry. A common element of these crises is how a number of initial failures preceded later collective failures.

The failure of a large bank can threaten the stability of the banking system, bank regulators have adopted several measures to prevent failures and to contain the "domino" or the contagion effect which may result from a failure. So the contagion is considered more problematic in the banking sector than in other industries.

Aharony and Swary (1983) show that when any given large bank encounters a financial crisis or failure, it causes society as a whole to lose faith in the banking system, thereby leading to withdrawal of funds from saving accounts, or a "runs on banks". Theses authors examine the contagion effects of three large failures Franklin National Bank of New York, United States National Bank of San Francisco, and Hamilton National Bank of Chattanooga. Using a sample of solvent banks grouped by deposit size, they found no evidence to support the pure contagion hypothesis. They conclude that failure due to factors such as fraud or mismanagement is entirely bank-specific, whereas failure due to more general causes, such as risky loans and investments, can precipitate a reaction by other banks that suffer from a similar risk exposure.

Akella and Chen (1990) indicate that the size of the institution introduces further complexities. It is generally argued that large banks are more likely to hedge financial risks due to economies of scale. Therefore, it follows that large banks are likely to be less sensitive to movements in financial markets, and especially interest rates. However, size is a relative feature and while banks may be large within a specific market, they may still be small on the international stage. Nevertheless, these arguments imply that the behaviour of stock prices may differ within the banking sector between large and small institutions even when faced with common economic conditions. Further evidence of the impact of the size of the institution is provided in Elyasiani and Mansur (1998) and Faff *et al*. (2005) who show that the interest rate exposure of large and small banks differs, especially in periods of differing regulation.

Demsetz and Strahan (1995) and (1997) show that there are significant differences in the diversification and financial leverage strategies of large and small banks. Larger banks are better diversified (geographically and product-wise) but also more highly leveraged and less liquid. As a result, larger financial institution tend to have a greater systematic risk (market beta) than smaller banks, although their overall risk (the sum of systematic and idiosyncratic risks), is not significantly different from the latter. Thus, while the overall level of a bank's total risk may not be affected directly by firm size, the composition of the bank's risk is clearly influenced by the firm's type of investments, diversification opportunities, and financial leverage decisions, all of which are typically influenced by the size of the bank.

Demsetz and Strahan (1997) also argue in favour of the dissimilarity of spillover between large and small financial institution. According to these authors, larger banks typically have greater exposure to systematic risk and commensurately lower idiosyncratic risk, compared to smaller banks, with idiosyncratic risk being typically related to local factors.

3. DATA CHARACTERISTICS

3.1. Data Description

Our aim of this study is to examine the banking south-east of Asia's sectors. Our sample consists in 123 banks established in five Asian countries (Thailand, Philippines, Malaysia, Korea and Indonesia) all listed in *SE ASIA-DS Banks*. The banking institutions chosen to conduct our test are commercial and mutual banks. Then the sample is disaggregated by size[1] into two portfolios for each country: Large and Small banks.[2]

So we investigate the intra-industry transmission of changes in the level and volatility of stock returns for 35 large banks and 88 small banks from five crises-affected East Asian countries: Indonesia, Korea, Malaysia, the Philippines and Thailand.

The breakdown of the data by country is as follows: 7 large banks and 19 small banks in Indonesia; 9 large banks and 16 small banks in Korea; 5 large banks and 19 small banks in Malaysia; 5 large banks and 15 small banks in the Philippines; and 9 large banks and 19 small banks in Thailand. (see Table 1)

Table 1. Overview of the Banking System by Country and by Size

	Large Banks	Small Banks	Total
Indonesia	7	19	26
Korea	9	16	25
Malaysia	5	19	24
Philippines	5	15	20
Thailand	9	19	38
Total	35	88	123

[1] Average market capitalization during 1995-1997 was used to rank all institutions in order to determine whether they qualify to be a part of the large bank portfolio. To be included in the large bank portfolio of Indonesia had to meet the following criteria: a market capitalization of greater than 72.124 million (Rp); for the large Korean's bank portfolio include a minimum market capitalization of 7.137 billion (won), similarly for the large bank of Malaysia, Philippines and Thailand the minimum requirement were respectively 2.76 million (Rg), 7.746 million (PH peso) and 82.984 (BHT).

[2] We don't exclude banks which failed in late of 1998.

Daily stock indices and individual bank stock prices for the 1995-1997 periods are taken from Data-Stream International. For each bank we compute the daily stock return over the period (December, 30, 1994 to December, 31, 1997), this provides a wide sample of 784 observations. The daily return is defined as $R_t = \log(P_t / P_{t-1})$; where P_t is the price on day t.

Within each market, the portfolio of banks is constructed on a value weighted basis[3] then we subdivided it into two categories on the basis of market capitalization; value weighted returns are then constructed for each of the large and small-medium bank portfolios within each market.

In addition, daily returns are constructed on the market for each country. Specifically the market indices used are: Indonesia Bank Stock Index, Korea Bank Stock Index, Philippines Bank Stock Index, Malaysia Bank Stock Index and Thailand Bank Stock Index.

The graph in Figure 1 shows that the price index reached its maximum value for Malaysia, Indonesia and Philippines in late 1996 and for Thailand and Korea in early 1996. We note also that these five series are characterized by a general trend downward.

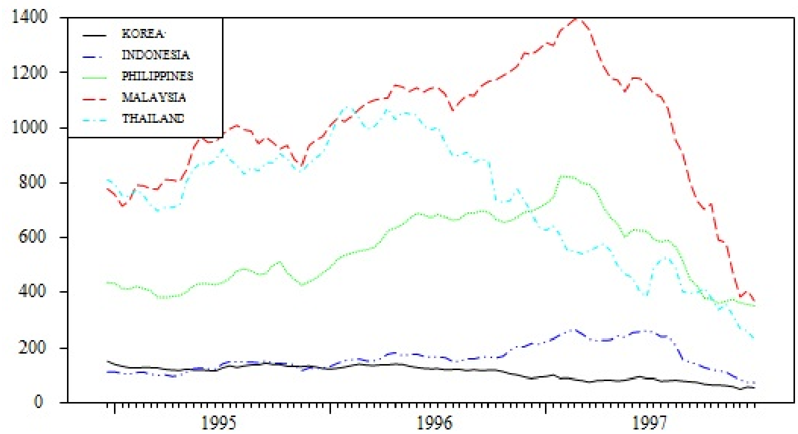

Figure 1. Changes in Price Index Over the Five Asian Countries from 1994 to 1997

[3] Value weighted bank stock index is generated by adding the prices of each of the bank in the index and dividing them by the total number of stock bank. Bank with a higher price will be given more weight, and therefore will have a greater influence over the performance of index. $P_t = \sum P_{it} K_i$, with $K_i = \frac{P_i \times NOS_i}{\sum P_i \times NOS_i}$; (NOS: number of shares). Finally the adjusted price data are transformed into period returns $R_t = \log \frac{P_t}{P_{t-1}}$.

3.2. Methodology and Model Specification

3.2.1. Modelling of the Spillover Effect

The tests in this note are based on the ARCH[4,5] family of models developed by Engle (1982) and Generalized (GARCH) by Bollerselv (1986). These models have been empirically shown to capture reasonably well the time variation in the volatility of daily bank stock returns. Moreover, we employ its multivariate form of model bank stock return and risk spillover effect within the banking industry.

The general GARCH (*p*,*q*) model can be described by the system of Equations (1)-(3) below:

$$y_t = \varphi x_t + \varepsilon_t , \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \alpha_j h_{t-j} , \tag{2}$$

$$\varepsilon_t / \Omega_{t-1} \sim N(0, h_t) , \tag{3}$$

where y_t is the stock return, x_t is the exogenous (or predetermined) vector of variables, ε_t is a random error, h_t is the conditional variance of ε_t and Ω is the information set. φ, α_0, α_i and β_i are parameter vectors or scalars with appropriate dimensions, and t is the time index.

The multivariate GARCH specification offers several advantages: first, it accounts for intra-industry transmission of bank stock returns and bank stock return volatility. This feature is to capture intra-industry information spillover between the large and small banks for each country. Second this specification allows the asymmetry of the spillover effect across the large and small to be investigated and tests of the linear

[4] The common feature of ARCH and GARCH models is that they specify the conditional variance as a function of the past shocks allowing volatility to evolve over time and permitting volatility shocks to persist. The distinction between these two methodologies is that while ARCH incorporates a limited number of lags in derivation of the conditional variance, GARCH allows all lags to exert an influence by including the past value of the conditional variance itself, in addition to the past values of the squared errors. Thus, ARCH models are considered to be short memory models while GARCH models are of the long memory category.

[5] All ARCH type models capture the tendency for shock persistence. A succinct measure of the shock persistence, as measured by the GARCH process, is the sum of the coefficients $\alpha_i + \beta_i$ which must be less than or equal to unity for stability to hold. If the magnitude of this sum is close to unity, the process is said to be integrated-in-variance, where the current information remains important for the forecasts of the conditional variance for all horizons (Engle and Bollerslev, 1986).

relationships among the parameters within and across the model equation to be carried out. That's why we extend our approach by suggesting two other nonlinear models such as E-GARCH (Nelson, 1991) and GJR-GARCH (Glosten, Jagannathan and Runkle, 1993). The conditional variance for these two models is described as follows.

E-GARCH:

$$\ln(h_t) = \alpha_0 + \alpha \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} + \gamma \left[\left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| - E\left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} \right) \right] + \beta \ln(h_{t-j}) . \quad (4)$$

GJR-GARCH:

$$h_t = \alpha_0 + (\alpha_i + \gamma I_{t-1})\varepsilon_{t-i}^2 + \beta_j h_t . \quad (5)$$

With $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $I_{t-1} = 0$ otherwise, in this study, we employ a five equation system GARCH (1,1) model (Eqs. (6)-(11) below) to describe the stock return (R_i) and conditional stock return volatility (h_i) behaviour of the two main categories of banks ($i = 1,2$); (respectively are large and small banks).

$$R_{1t} = a_1 + b_1 RM_t + c_1 R_{2,t-1} + \varepsilon_{1,t} , \quad (6)$$

$$h_{1t} = v_1 + \alpha_1 h_{1,t-1} + \beta_1 \varepsilon_{1,t-1}^2 + \lambda_1 h_{2,t-1} , \quad (7)$$

$$R_{2t} = a_2 + b_2 RM_t + c_2 R_{1,t-1} + \varepsilon_{2,t} , \quad (8)$$

$$h_{2t} = v_2 + \alpha_2 h_{2,t-1} + \beta_2 \varepsilon_{2,t-1}^2 + \lambda_2 h_{1,t-1} , \quad (9)$$

$$\varepsilon_{j,t} / \Omega'_{t-1} \sim N(0, h_{j,t}) , \quad (10)$$

$$h_{ij,t} = \rho_{ij} h_{i,t} h_{j,t} (-1 < \rho_{ij} < 1) . \quad (11)$$

In the above specification index i ($i = 1,2$) represents respectively large and small banks, t is a time index, ε_i denotes the error term with the properties described by Eq. (10), and Ω'_{t-1} is the information set. The conditional variance-co-variance relationship, specified by Eq. (11), is a constant correlation model which permits the variances to change but requires the correlation (ρ_{ij}) between the series to be constant.[6]

The value of (ρ_{ij}) needs to be estimated along with the model parameters. The coefficients α_i and β_i in Eqs. (7) and (9) must satisfy stationary conditions such that ($\alpha_i > 0$), ($\beta_i > 0$), and $(\alpha_i + \beta_i) < 1$. The sum $(\alpha_i + \beta_i)$ serves as a measure of shock persistence in the respective industry.

Eqs. (6) and (8) in this model, presented as extended market models, describe the return generating process and are functions of the market return (RM) and the return spillover effects across the two banking categories. The cross- return terms allow for explicit testing of the extent of return interdependence among the bank sector.

The volatility's equation (Eqs. (7) and (9)) extends the traditional GARCH specification by including the risk spillover (h_{it} and h_{jt} , $i \neq j$) across the two groups of banks. This specification of the volatility equation permits us to test the prevalence of risk spillover among the banking sector.

Empirical analysis of the spillover issues sheds light on the transmission mechanism of risk and return across financial industries. Specifically, we try here identifying the direction and the strength of the spillover effect, indicating whether a unidirectional or a bidirectional causality mechanism is in effect. Unidirectional spillover demonstrates a leadership-followership pattern across the two categories of banks considered and can help determine the predictability of the followers' stock returns.

Finally, this analysis has implications for banks' diversification strategies and the formulation of an effective regulatory policy. For example, if risk transmission is found to be unidirectional from large banks to small banks rather than in the opposite direction, then legislators and investors should take this asymmetric risk spillover into account when devising new regulations and making investment decisions, respectively.

3.2.2. Spillover Excess or "CONTAGION"

Another formulation of our model consists to put a new regressor in all Equations (7, 8, 9, 10), we introduce Dum_t : dummy variable to take the event (non crisis and crisis periods) into account.

Determination of Crisis Period

[6] Other specifications such as VECH-GARCH model proposed by Bollerslev *et al*. (1988) fail to ensure that the conditional variance-co-variance matrix of returns are positive semi-definite. The constant correlation GARCH model suggested by Bollerslev (1990) is an alternative specification to ensure a positive semi-definite conditional variance co-variance matrix. For a discussion of the constant correlation GARCH model, see Kroner and Sultan (1993) and Park and Switzer (1995).

In order to detect the triggering of the crises in the banking sector and the appearance of structural change in the process of volatility, we use the test of structural breaks based on Chow's test, considering a heteroscedastic variance.

Specifically, T is a period that contains a breakpoint at time t which subdivides the period into two periods S1 and S2. Let β_1, β_2 vectors of estimated parameters of each process of the conditional variance and Ω_1 and Ω_2 their variance covariance matrices of the respective parameters. Under the hypothesis that β_1 and β_2 are independent and normally distributed, the difference $\beta_1 - \beta_2$ is zero mean and the variance is equal to $\Omega_1 + \Omega_2$.

So the Wald's test of the null hypothesis of no significant structural change is given as follows:

$$Wald = (\beta_1 - \beta_2)^T (\Omega_1 + \Omega_2)^{-1} (\beta_1 - \beta_2) .$$

Under the null hypothesis of no structural change H_0, the Wald's statistic follows asymptotically $\chi^2(p)$, with p degrees freedom, where p is the number of coefficients estimated in the vector of parameter β_1.

It is necessary to note the importance of the large number of observation or size of the interval of crisis in the test of contagion, which can significantly affect the results of our tests (Dungey and Zhumabekova, 2001).

By a recursive method, it's possible to make vary the breakpoint on the entire interval until the detection of significant structural change. (See Caporale, Cipollini and Spagnolo, 2005).

Transmission Test in Crisis Period

The turbulent (crisis) event binary (Dum_t) takes the value of unity if the sector is on crisis, zero otherwise. This new regressor allows capturing an excess of transmission (spillover) that can exist in crisis period: a phenomenon which we called by **"Contagion"**.

Our new specification becomes:

$$R_{1t} = a_1 + b_1 RM_t + c_1 R_{2,t-1} + d_1 R_{2,t-1} Dum_t + \varepsilon_{1,t} , \tag{12}$$

$$h_{1t} = v_1 + \alpha_1 h_{1,t-1} + \beta_1 \varepsilon^2_{1,t-1} + \lambda_1 h_{2,t-1} + \theta_1 h_{2,t-1} Dum_t , \tag{13}$$

$$R_{2t} = a_2 + b_2 RM_t + c_2 R_{1,t-1} + d_2 R_{1,t-1} Dum_t + \varepsilon_{2,t} , \tag{14}$$

$$h_{2t} = v_2 + \alpha_2 h_{2,t-1} + \beta_2 \varepsilon_{2,t-1}^2 + d_2 h_{1,t-1} + \theta_2 h_{1,t-1} Dum_t \,, \tag{15}$$

$$\varepsilon_{j,t} / \Omega'_{t-1} \sim N(0, h_{j,t}) \,, \tag{16}$$

$$h_{ij,t} = \rho_{ij} h_{i,t} h_{j,t} (-1 < \rho_{ij} < 1) \,. \tag{17}$$

In this case, to test the existence of contagion within the banking sector in crisis period requires testing nonentity of parameters d_i and θ_i. So we construct the tree tests below:

T1: Test of contagion return from large to small size banks

$$T_1 : \begin{cases} H_0 : d_1 = 0 \\ H_1 : otherwise \end{cases} .$$

T2: Test of contagion volatility from large to small size banks

$$T_2 : \begin{cases} H_0 : \theta_1 = 0 \\ H_1 : otherwise \end{cases} .$$

T3[7]: Test of contagion from large to small size banks

$$T_3 : \begin{cases} H_0 : d_1 = 0 \; and \; \theta_1 = 0 \\ H_1 : otherwise \end{cases} ;$$

H_0: null hypothesis of no contagion from large to small size bank.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

4.1.1. Properties of the Data

Figure 2 represents the evolution of the returns' index of large banks, small banks and the market return in five Asian countries. It shows that these series are highly volatile. There are also groupings of volatility: the large variations tend to be followed by large variations, and small changes had been followed by other small changes. The

[7] T_3 is made in the form of test's restriction of Wald on the parameters, with the heteroscedastic variance.

volatility is evolving over time. This suggests that ARCH/GARCH-type process could be adapted for modelling these series.

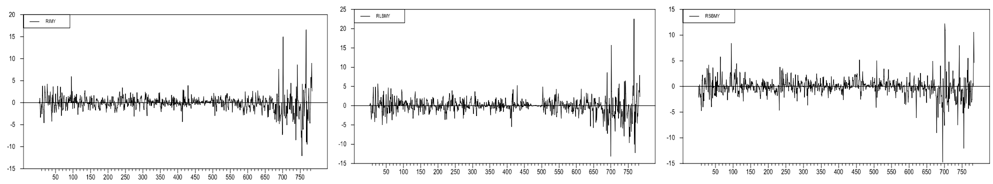

Figure 2.a. Malaysia (RIMY-RLBMY-RSBMY)

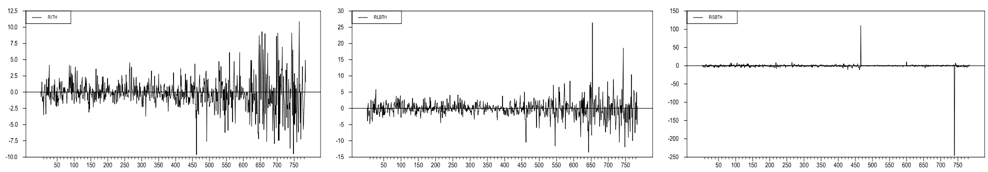

Figure 2.b. Thailand (RITH-RLBTH-RSBTH)

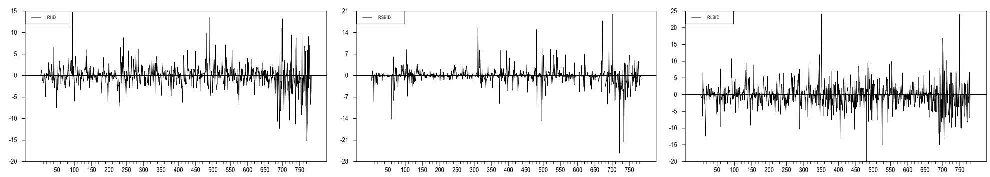

Figure 2.c. Indonesia (RIID-RSBID-RLBID)

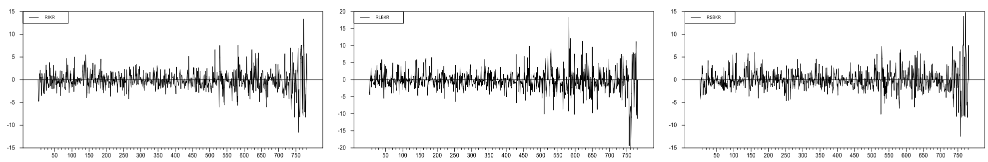

Figure 2.d. Korea (RIKR-RLBKR-RSBKR)

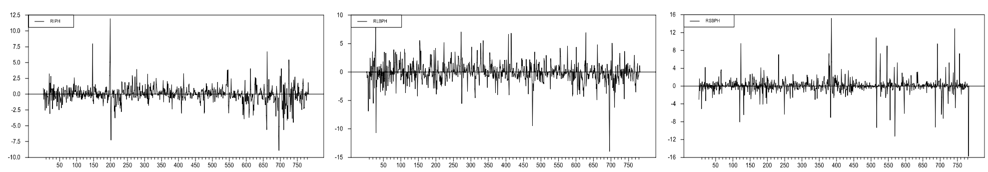

Figure 2.e. Philippines (RIPH-RLBPH-RSBPH)

Figure 2. Evolution of Market Return (RI) and Return Index of Large (RLB) and Small Banks (RSB) Over the Five Asian Countries

To investigate the appropriateness of the GARCH framework certain properties of the data such as normality, white noise, skewness, and kurtosis have to be examined. The extant literature generally assumes that the error term is normal and that it follows a strict white noise process. These two assumptions are tested here using the Lagrange multiplier (LM) test and the Box-Ljung portmanteau test, respectively.

Descriptive statistics associated with the bank stock returns and the statistics for the test procedures are presented in Table 2.

According to the Table 2, the banking sector in all countries has exhibited a negative average return (except Philippines's small banks, which the average rate is 0,0414). In all five markets, return on the bank portfolio have been more volatile, as manifested through the standard deviation estimates, then the return on the corresponding market index. This is not surprising because, in this sample, we find a turbulent period.

Additionally, this table shows that the average rate of return of large banks in both Indonesia and Malaysia is higher than that of small size banks; large banks also have a higher average rate of return than the market average rate of return (in two countries). Also, the standard deviation of the rate of return for large banks is higher than that of small sized banks and the market.

In relation to Korea, the average rate of return and its standard deviation on the sector, as well as the large and small sized portfolio are all lower than the market rate of return. In addition, the average rate of return of small banks is higher than large banks; in contrast its standard deviation is smaller than large sized banks. This shows that small banks have higher return and sustain a lower amount of risk.

The Philippines and Thailand banking sector experienced some extreme returns over the sample period. The average rate of return of the Philippines's small banks is higher than that of large sized banks with a higher standard deviation. This shows that those small banks have higher return and sustain a higher amount of risk. This phenomenon is very similar to that of Thailand.

For all portfolios (except Korea), the unconditional distributions of returns are non-normal as evidenced by significant skewness and kurtosis, as well as significant Jarque-Bera statistics. The significant kurtosis values indicate that the distributions of all return series are leptokurtic.

To identify whether the time series of portfolio returns and the market index are stationary, the Augmented Dickey-Fuller (ADF) unit root test is used. The findings indicate that all stock return series with their corresponding market index follow an I(0) process, and thus are considered stationary.

The test statistics for the return reject the null hypothesis of no autocorrelation (with Ljung-Box *Q*-test) and no ARCH effect (with ARCH LM test), respectively, for all portfolios (except Thailand). These findings suggest that a GARCH-type process is indeed appropriate for modelling banking stock return.

Table 2. Descriptive Statistics

	Indonesia			Korea			Malaysia		
	Large	Small	Market	Large	Small	Market	Large	Small	Market
Sample Mean	-0.1742	-0.1877	-0.1606	0.1843	-0.1555	-0.1283	-0.0714	-0.0778	-0.0784
Standard Deviation	0.1429	0.13125	0.0977	0.0958	0.0866	0.0791	0.0787	0.0589	0.0705
t-statistic	-1.0314	-1.4036	-0.6208	-1.9230	-1.7965*	-1.6225*	-0.9081	-1.3220	-1.1113
Skewness	0.6030***	-1.7481***	0.0412	-0.04251	0.0218	0.2532***	0.7822***	-0.273***	0.7179***
Kurtosis	12.5524***	29.4896***	6.3399***	4.080***	4.7001***	4.5701***	16.6236**	12.862***	15.2498***
Jarque-Bera	5187.97***	28770.81***	1311.59***	543.55***	720.80***	689.78***	9095.61***	5407.22***	7654.46***
Q4	30.647***	37.734***	-	7.842*	18.673***	-	13.854***	29.702***	-
Q8	34.715***	35.923***	-	14.619*	36.288***	-	16.256**	47.626***	-
Q12	42.923***	39.828***	-	22.181**	58.252***	-	30.959***	51.461***	-
LM	42.827***	71.621***	-	54.864***	102.306***	-	112.517***	59.111***	-
DF	-26.353***	-25.993***	-24.547***	-26.28***	-25.476***	-24.75***	-24.870***	-23.293***	-23.974***

	Philippine			Thailand		
	Large	Small	Market	Large	Small	Market
Sample Mean	-0.1520	0.041	-0.0257	-0.2172	-0.1268	-0.1582
Standard Deviation	0.0796	0.0833	0.0513	0.1025	0.2708	0.0847
t-statistic	-1.908*	0.4975	-0.5014	-2.1183	-0.4683	-1.8673*
Skewness	-1.0502***	-0.727***	0.3127***	0.762***	-18.169***	0.2338***
Kurtosis	9.635***	45.54***	11.6768***	9.982***	518.731***	3.8830***
Jarque-Bera	3173.15***	67732.63***	4461.16	3327.29***	88219.31	499051***
Q4	11.196**	12.928	-	17.269***	1.675	-
Q8	13.323*	14.455*	-	21.014***	2.542	-
Q12	14.055	21.079**	-	36.939***	2.743	-
LM	12.284*	2.731	-	3.341	0.0093	-
DF	-24.876***	-25.485***	-21.610***	-24.435***	-28.060***	-25.128***

Note: * significant at a 10% significance level, ** significant at a 5% significance level, *** significant at a 1% significance level.

4.1.2. *Selection of Model Specification*

Before proceeding with the ARCH modelling process, we first examine the appropriate ARMA (p,q) specification for each of the banking series using the variance Jarque-Bera, Ljung-Box and Q-test to determine the model.[8] The preferred lag length is established from the Akaike information criterion. The appropriate lag is then used in the conditional mean equation. The results are detailed in Table 3.

After verification that ARCH or GARCH effect exists, we apply 3 models GARCH (1,1), E-GARCH (1,1) and GJR-GARCH (1,1). The finding indicates that the most appropriate for each market is GARCH (1,1). The detail is presented in Table 3.

Table 3. Selection of the Model

	Indonesia		Korea		Malaysia		Philippine		Thailand	
	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small
Conditional Average										
AR(1)	-2193	-2121	-1879*	-1799	-1720*	-1483*	-1731	-1770	-1924*	-2690*
ARMA(1,1)	-2187*	-2113*	-1821	-1794	-1743	-1486	-1730	-1774	-1935	-2689
MA(2)	-2189	-2122	-1790	-1790*	-1721	-1488	-1729*	-1765*	-1927	-2693
Conditional Variance Equation										
Garch	3.29	3.35**	2.81**	2.514**	1.97**	1.73**	2.53**	2.48	2.95**	2.95**
E-Garch	3.30**	3.18	2.81	2.51	1.96	1.67	2.53	2.50**	2.92	2.92
GJR-Garch	3.28	3.34	2.80	2.50	1.95	1.621	2.53	2.47	3.94	2.94

Notes: * The appropriate model is chosen by AIC. **The appropriate model is chosen with the regard of maximum log-likelihood.

4.2. Multivariate GARCH Results

4.2.1. *Spillover Analysis*

a) Systemic Risk (Market Beta)

The b coefficient provides the relation between the returns on the bank portfolio and the market portfolio and is akin to a beta estimate in market model, in the theory, we

[8] The diagnosis of residual series, from a modelling AR (1), ARMA (2,2), and MA (1) is given by the statistic Jarque-Bera which shows that non-normality of the series, while the statistic Ljung-Box Q (20) may indicate serial correlation. However, the Statistic Q^2 (20) residues square show correlations of second order, suggesting a time dependence of variance. Heteroscedasticity of variance was confirmed by the statistical test for the presence of ARCH effect.

expect *b* positive. In spite of this statement, the Table 4 shows that the market beta for small banks in Indonesia, Malaysia and Thailand exhibited a negative value. This finding suggests that the return of these banks' portfolios inversely follows the market. (The return decreases in value if the market goes up).

In other side, as shown in Table 4, systemic risk in all portfolios is highly significant. In terms of magnitude, the market beta is all below unity with Thailand large banks having a highest market beta (1,112) that is greater than 1; in fact the large level of beta is possibly due to their assumption of greater credit risk, higher financial leverage, more extensive engagement in risky off balance sheet activities (e.g., trading and derivative positions), and the more aggressive attitudes of their managers toward risk.

In comparison between the large and small banks' market beta, the systemic risk exposures of the large banks are significantly higher (except the Philippines). This is not surprising because the all large banks' portfolios is dominated by the much greater number of smaller banks. The finding that large banks take on greater market risk than their smaller counterparts is consistent with Elyasiani, Mansur and Pagano (2007).

b) ARCH and GARCH Effects and Shock Persistence

The ARCH parameter β_i and the GARCH parameter α_i are positive and significant in all portfolios, satisfying the specified requirement of non-negativity for all of the models. The magnitude of β_i , which embodies the effect of the previous surprises, is found to be much higher than that of the parameter α_i , which shows the effect of the last period's shock directly. The implication is that the market has a memory shorter than one period and that volatility is less sensitive to its own lagged values than it is to new surprises in the market place.

The sum of the ARCH and GARCH parameters provides a measure of persistence of shocks for each set of banking institutions. This sum is found to be less than unity for all portfolios consisting with the stationary condition of a GARCH model.

As can be seen in Table 4, shock persistence for the large bank varies over (0.131-0.303) range and is lower than that for smaller banks (0.02-0.338). The small value of the persistence measure is an evidence that shocks to the banking sector have lowly persistent effects and that the response function of volatility decays at a relatively fast pace.

Among the five countries, the returns of smaller banks exhibit the widest gap in terms of persistence with those of the large banks. This indicates that the latter group of banks seems to be better able to absorb the shocks to which they are subjected. This isn't surprising given because the stock of large banks is generally more liquid than the stock of small banks.

c) Return Related Spillover Effects

Eqs (6) and (8) enable us to test whether there are return-related spillover effects across large and small bank. In table 4, the parameters c_1 and c_2 in the mean return equation represent return-related spillover effects. If either of these two parameters is significantly different from zero, we can conclude that return spillover exists.

Coefficients estimated in Panel A demonstrate that the evidence is consistent with return spillover effect within the industry. The coefficient estimates of c_1 and c_2 are positive and significant in both sub-portfolios. We notice also that there is a significant bidirectional, but asymmetric effect with large bank portfolio exerting a stronger influence on the small bank portfolio and vice versa. This so called industry effect is quite strong as indicated by the size of the coefficient estimate. The finding is consist with a view of the larger banks are market leaders

Similar to Panel A, the Table 4 with Panel B, also demonstrates that large and small banks show return interdependence (c_1 and c_2 parameter are also positive and significant) indicating the direct co-movement of return across the industry. In terms of magnitude of the effects, the coefficients estimated indicate that the small banks have a big effect on large size banks. This result suggests that small banks are leader in term of return related shocks across the bank sector of Korea. This finding can explained by: the government controlled a great number of large banks through a majority share counter only three small banks which were controlled by public entities; that is why they are more competitive in the market.

As with two previous Panels A and B, Panel C also shows that the evidence is consistent with a spillover effect across the banking industry. The relevant coefficient estimate is positive and significant in both sub-portfolios. Again the return spillover from the large to the small banks is larger than the spillover from the small to the large banks, which is consistent with a view of Panel A (Indonesia) and the view of larger banks as market leader.

In contrast to the three first panels above, Panel D, reports the evidence in favour of prevalence of stock return transmission among the industry banks, however, we also find that there is evidence of feedback on return from larger to smaller banks, with a significant negative coefficient of c_2, implying that an increase in the return of large bank size is associated with a subsequent decrease of small banks. The negative sign may be an indication of rivalry between the two groups of banks.

Finally, as well as Panel A, C and D, Panel E shows that Thailand's large bank have a great level of effect upon small bank size banks. This indicates also the feature of large banks as leader market.

To resume, our finding is: the spillover effect within the industry is strong for each market with the greatest influence running from the large to the small banks (except Korea). This result is not surprising because generally large banks represent a greater mix of industries than those of small, both because large banks are likely to have expertise in a wider variety of borrower industries and because they are more active than small institutions in the secondary market.

d) Risk Related Spillover Effects

Eqs (7) and (9) in the model allow us to identify potential risk-related spillover effect. The parameters λ_1 and λ_2 in Table 4, Panels $\mathrm{A} \rightarrow \mathrm{E}$ measure the magnitudes of theses effects. Similar to the above discussion of return-related spillover, if either of these two parameters is significantly different from zero, we can conclude that there are spillover effects between the volatilities of the large and small size banks.

As can be seen from a review of the λ_1 and λ_2 parameters estimated in Table 4, Panel A and B show that evidence of significant risk spillover within these industries (Indonesia and Korea). However we also found that there is evidence of feedback in volatility across the industry with a significant negative spillover coefficient λ_1 and λ_2; indicating that increased uncertainty in the large (or small) bank's portfolio will lead to decline in volatility in the return of its counterpart portfolio. This may be an indication that disquiet in one of the group market, derives their corresponding less riskier customer to seek the same product from the other group, leading to the fall of its volatility' portfolio.

In contrast Panel C, indicates that there is evidence of bidirectional volatility spillover between large and small bank's portfolio. The coefficients λ_1 and λ_2 are positive and significant in both sub-portfolio, that is, innovations that are manifest in volatilities (risks) in the large bank portfolio have an influence over the volatilities on the small bank portfolio and vice versa. This finding indicates that in Malaysia, the large banks are the leaders in terms of volatility transmission; so we can add this explanation: the leadership of large banks in terms of volatility transmission can be due to the fact that large banks have had less stock return volatility than the smaller banks. Thus any increase in the riskiness of large banks is important "new" which is quickly propagated to other small banks.

As shown in Table 4, Panels D and E indicate also that there is strong evidence of volatility spillover within the each industry (both Philippines and Thailand). The λ_1 and λ_2 parameters are significant, but only λ_2 is negative indicating the presence of the unidirectional feedback in the volatility from the large bank riskiness to smaller banks. In this case, a decrease in large portfolio risk leads to a higher risk at smaller banks but not the other way around. The negative sign may be an indication of rivalry across these industries.

Overall, we can conclude that the strong of volatility spillover effects across the industry confirms the intuition that: these institutions typically assume less localized, less idiosyncratic risks and possibly due to more geographic and product diversifications.

Table 4. Spillover of Risk and Return Among Sized Banks in Each Country

	Indonesia (Panel A)		Korea (Panel B)		Malaysia (Panel C)		Philippine (Panel D)		Thailand (Panel E)	
	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small
a_i interceprt	1.43*	-1.51*	0.130*	-0.09*	-0.005*	0.007*	0.103*	0.146*	1.781*	-7.36*
b_i Market	0.003*	-0.003*	0.221*	0.168*	0.632*	-0.855*	0.507*	0.714*	1.112*	-4.58*
c_i cross-return	0.948*	1.05*	1.317*	0.759*	0.740*	1.351*	-0.70*	-1.408*	0.243*	4.12*
V_i intercept	8.22*	-1*	1.797*	1.033*	0.75*	1.36*	2.871*	5.691*	-0.05*	108.28*
α_i Garch	0.022*	0.046*	-0.022*	-0.133*	0.037*	0.065*	0.0017*	0.273*	0.253*	0.0019*
β_i Arch	0.28*	0.27*	0.119*	0.119*	0.171*	0.171*	0.164*	0.164*	0.0008*	0.0008*
λ_i cross volatility	-0.012*	-0.041*	-0.46*	-0.08*	0.04*	0.08*	0.123*	-0.002*	0.0044*	-0.628*
$\alpha_i + \beta_i$ Persistance	0.303	0.326	0.131*	0.242*	0.209*	0.237*	0.182*	0.338*	0.253*	0.0019*

Note: *Already reached 1% of significance.

4.2.2. *Measuring Contagion*

a) Selecting of Breakpoints

Before the beginning the study of contagion (spillover excess) we need to seek the non-tranquil period for each country. We use for this purpose a "recursive" test to select the breakpoints in the volatility based on *Chow* test. In fact this test indicates the start of the period crisis by accepting the hypothesis H0: there is no change structure in volatility in date *T*.

The estimated of breakpoints reported in Table 5, show that turbulent period started to occur earliest the beginning of July 1997 when the Thailand Baht was devaluated (that it's the first symptom of financial Asian's crisis). In most case the turbulent period seems to coincide (at the earliest) with the anticipation of the crisis in the beginning of 1997.

Table 5. Selection of Breakpoints

Country	Chow Test	Beginning
Indonesia	7.119**	1996/12/31
Korea	0.381*	1996/04/01
Malaysia	0.102*	1996/07/01
Philippine	0.396*	1996/07/01
Thailand	0.656*	1997/04/01

Note: *significant at a 10% significance level, ** : significant at a 5% significance level.

b) Tests of Contagion

The introduction of the turbulent period may have had significant effects on the level and volatility of stock returns for both large and small banks of each country. In theory, it can be argued that the magnitude of this event effects will be different among the these two categories of banks

The d_i and θ_i parameters in the model capture the effects of the turbulent period on the level and volatility of stock returns, respectively. By using the bivariate model (Eqs 12-17), the results of the estimations are given in the Table 6 and the following remarks are retained.

In relation to Indonesia, contagion started to occur at the beginning of 1997, we find that there is a highly significant negative excess of spillover in return from the large to small sized banks. The evidence of contagion in volatility is even more pronounced with a wide influence of large banks towards small sized banks. The coefficient estimated θ_1 is approximately equal to 1.15, so based on this parameter value, we can confirm that an increase of the 10% of the volatilities of the large bank's portfolio is translated by an increase of 15% of small banks' risks.

In Korea, we notice that there's neither contagion in return on contagion volatility within the industry. The lack of contagion can be attributed to this factor: the occurrence of the turbulent event with the anticipation of crisis for this sector, increased investor's perception of the risk, that's why new regulation appears and may make more difficult for smaller to survive in the face of the competitor of the bigger (as well as implicit TBTF).

Concerning Malaysia, we find evidence of contagion across the industry, specifically, with the regard of these parameters d_i and θ_i , it appears that the large banks have a contagious influence only on volatility.

When we looked at the possibility of contagion effect from the large to the small banks of the Philippines, we found evidence of feedback contagion in volatility from large size banks to small size banks; in other word, the increase of the volatility in large bank's portfolio contributes to calm the small bank's portfolio. With Thailand, the results also shows that evidence is consist with a contagion effect within the industry.

The results reveal a main finding that the contagion effect within the industry is strong for each market with the greatest influence running from the large banks to the smaller banks.

Table 6. Estimated Coefficients of Transmission in Turbulent Period

	Indonesia		Korea		Malaysia		Philippine		Thailand	
	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small
c_i	0.670***	0.62***	4.061**	0.219**	0.297**	1.33	-0.486***	-0.179***	0.363***	1.96***
d_i	-0.239*	-0.096**	0.00049	-0.021	-0.128**	-0.039	0.048**	0.276***	-0.044***	0.345***
λ_i	-0.013**	0.086***	0.051	-0.047*	0.065**	0.591	0.089**	-0.038***	0.003***	0.775***
θ_i	0.091**	0.151***	0.050	-0.008	0.071**	0.424	0.024*	-0.487***	0.003***	1.093***
T:$H0$: No Contagion	526.96***		17.94		2812.09***		367.069***		573.97***	

Note: * significant at a 10% significance level, ** significant at a 5% significance level, *** significant at a 1% significance level.

5. CONCLUSION

In this note we investigate return and volatility spillover effects between large and small bank's portfolio established in five countries in Asia, thus, we have applied the multivariate GARCH (1,1) model of stock returns in the banking industry across the five Asian markets. The purpose the analysis has been to explore the risk-return relation within the industry of each market.

There are two aspects of this analysis: first, the study has examined the relation between risk and return, thereby incorporating time variation in the volatility and intra-industry spillover within the banking sector. Second we have extended our analysis by introducing a dummy variable to take into account the impact of turbulent period, this last enable us to capture the excess of spillover effect (so called contagion).

Our main finding is that interdependencies do exist in all five countries and they are higher size sensitive. The higher significance of the spillover effects suggests that intra-industry competition is in effect among large and small sized banks. In most cases, we notice that the small institutions are found to display stronger risk-related transmission (spillover volatility) while large institutions exhibit more pronounced return-related linkage.

With the regard to industry contagion effect, stock return of large and small size banks affect each other (except Korea), this shows that industry effect is quite strong in Indonesia, Malaysia, Philippines and Thailand. The findings are consistent with the view that these banking industries are partially segmented from the global market.

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Mailing Address: Wided Ben Moussa, Universite Paris-Ouest Nanterre, France. Tel: 3366 855 9286. E-mail: wbenmous@u-paris10.fr.

Received October15, 2012, Revised July 16, 2013, Accepted January 20, 2014.