BANK VOLATILITY CONNECTEDNESS IN THE SEACEN REGION

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The SEACEN Centre

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FOREWORD

The global financial crisis of 2008-09 affected many countries and markets around the world, including the SEACEN region. Financial institutions played a key role in the evolution of the US financial crisis and its transformation into a global one. Disproportionate risks taken by large financial institutions have, over time, caused serious trouble for the global financial system.

The SEACEN research project on "The Measurement and Monitoring of the Systemically Important Financial Institutions in SEACEN Economies" studies how stock return volatility shocks to global systemically important financial institutions and major banks in the SEACEN region were transmitted to other banks in and out of the region. In particular, the study applies the Diebold-Yilmaz Connectedness Index methodology to daily bank stock return volatilities and analyzes the bank volatility connectedness in the SEACEN region during the period from 2004 to 2016. The study finds that SEACEN bank stock return volatilities have been significantly affected by the global financial crisis as well as the European debt and banking crisis. The report identifies economy-level clusters in the banking volatility network. During systemic events, the region's bank volatility network becomes tighter with banks from different economies of the region generating volatility connectedness to others.

The research was conducted by Kamil Yılmaz, Professor of Economics at Koç University, Turkey, and Visiting Research Economist at SEACEN during FY 2016.

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Dr. Hans Genberg
Executive Director
The SEACEN Centre
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EXECUTIVE SUMMARY

The global financial crisis of 2008-09 struck the modern capitalist system like no other in recent history. It affected many countries and markets around the world, leading to global recession in 2009. Financial institutions played a key role in the evolution of the global financial crisis. Disproportionate risks taken by big financial institutions have, over time, caused serious challenges for the whole financial system.

News about the problems of a major bank led investors to flee the stocks of that bank first, followed by the stocks of other banks in the economy. Furthermore, depending on the size of the banking system and its financial connectedness with banks in other economies, news about the troubles of the banking system in a single economy forced investors to flee from banking sector stocks, not only in that economy, but in other economies of the region as well. In view of this, banking stocks are connected not only within one economy but across economies.

Financial centers around the world were affected by the US and European financial crises. The SEACEN region was no exception. This study applied the Diebold-Yilmaz Connectedness Index methodology to major SEACEN bank stock return volatilities to analyze the bank volatility connectedness in the region during the period from 2004 to 2016.

The results provide important insights into the behavior of the region's major bank stocks over time. First, economy-level clusters in the banking volatility network are identified. Second, the volatility connectedness of the SEACEN banks increased significantly when the US and European financial crises hit the worldwide financial markets. During systemic events, the region's bank volatility network becomes tighter with banks from different economies of the region generating volatility connectedness to others. When included in the analysis, along with the major Australian and Japanese banks, the global systemically important banks (GSIBs) from the US and Europe generate substantial volatility connectedness to SEACEN banks.

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1. Introduction

The global financial crisis of 2008-09 struck the modern capitalist system like no other in recent history. It took several stages that lasted a year and a half, before the crisis that originated in the US subprime mortgage market was transformed into a financial crisis on a global scale. It affected many countries and markets around the world, leading to global recession and a sharp contraction in the world trade in 2009.

That was not all. As the US financial crisis appeared to be in the ebbing in the second half of 2009, peripheral EU member countries started to face serious troubles in their financial systems. The European whirlwind involved more than just financial institutions with constantly worsening balance sheets: This time around, the governments were caught in the eye of the storm as well.

Financial institutions played a key role in the evolution of the crisis and its spread around the world. Disproportionate risks taken by big financial institutions have over time caused serious trouble for the whole financial system. The shock waves that originated in the US and, to some extent, the European financial markets spread throughout the globe within days if not hours. All global financial centers got affected. The SEACEN region was no exception.

In this report, our objective is to analyze the volatility connectedness across the major SEACEN region banks over a period that covers both the US and European financial crises. We would like to understand how major SEACEN region banks contributed to the evolution of the financial systemic risk in the region. In particular, we measure and analyze the dynamic volatility connectedness of major SEACEN region bank stocks from January 2004 through December 2016. The paper is an attempt to show that the Diebold-Yilmaz connectedness index (DYCI) framework can be very helpful to analyze how idiosyncratic and common shocks can spread among the financial institution stocks over time.

This study of the major bank stocks is motivated by the developments on the ground. The news about the troubles of a major bank lead investors to flee the stocks of that bank first, followed by the stocks of other banks in the economy. Furthermore, depending on the size of the banking system and its financial connectedness with banks in other economies, the news about the troubles of the banking system in a single economy force investors to flee the banking sector stocks not only in that economy but in other economies of the region as well. As a consequence, the banking stocks become connected not only in one economy but across economies.

There are several important contributions to the literature on the measurement of connectedness of financial firms. Among these, one can include the correlation-based measures. However, as they measure only pairwise association and are based on linear Gaussian distributions, they are of limited value in understanding connectedness of financial firms that lead to systemic risk. Recent contributions to the literature offer alternative approaches to study financial firm connectedness in a multivariate setting. The equi-correlation approach of Engle and Kelly (2012), for example, effectively focuses on average pairwise correlation. The CoVaR approach of Adrian and Brunnermeier (2016) and the marginal expected shortfall (MES) approach of Acharya et al. (2010) go beyond pairwise association, tracking association between individual-firm and overall-market movements, in one direction or the other.

There are other important contributions to the literature as well. Among those, Barigozzi and Brownlees (2013) propose a two-step lasso procedure which allows the decomposition of the long-run linkages into the dynamic and contemporaneous dependence relations. Dungey et al. (2013), on the other hand, rely on Google's PageRank Algorithm to develop a measure of the systemic risk and rank systemically important financial institutions. In another contribution, Black et al. (2013) specifically focus on the measurement of systemic risk in the European banking sector. It proposes a systemic risk measure, called "distress insurance premium," that can be used to identify a financial institution's contribution to the total capital shortfall of the financial system during a crisis. They show that the European banking systemic risk measure reached its highest level in late 2011.

All alternative approaches to the measurement of connectedness reviewed above are certainly of interest, but they measure different things, and a unified framework remains elusive. As argued by Diebold and Yilmaz (2014) and shown in the remainder of this paper, the DYCI approach provides such a framework. In Section 2, we provide a detailed exposition of the DYCI framework as developed by Diebold and Yilmaz (2014) and Diebold and Yilmaz (2012). The empirical analysis proceeds in four steps. In Section 3, we describe the data that is used to measure bank volatility connectedness across the major SEACEN region banks from January 2004 to December 2016. Next, in Section 4, we provide detailed information about the methods used to estimate the vector autoregression model in a large dimensional framework. Then, in Section 5, we perform a full-sample (static) analysis, in which we effectively characterize the unconditional connectedness across the major banks of 10 economies in the SEACEN region. This is of intrinsic interest, and it also sets the stage for Section 6, where we perform a rolling-sample (dynamic) analysis of conditional connectedness. As our ultimate interest lies there, we monitor how the daily volatility connectedness evolve over time, sometimes gradually and sometimes abruptly.

2. The Connectedness Index Methodology

This section provides a summary of the Diebold-Yilmaz connectedness index methodology, which was developed in a series of papers (Diebold and Yilmaz, 2009, 2012, 2014). The connectedness index is built upon the variance decomposition matrix associated with a covariance stationary N-variable vector autoregregression (VAR(p)):

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{1}$$

where p is the maximum lags of the endogenous variables included in the vector autoregression and $\varepsilon_t \sim (0, \Sigma)$.

The moving average representation of this N-variable VAR(p)

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

where the NxN, coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + ... + \Phi_p A_{i-p}$, with A_0 an NxN identity matrix and $A_i = 0$ for $i < 0$. The moving average coefficients (or transformations such as impulse response functions or variance decompositions) are the key to understanding the dynamics. We rely on variance decompositions, which allows us to split the forecast error variances of each variable into parts attributable to the various system shocks. Variance decompositions also allow one to assess the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall I \neq j$, for each i.

A study of the financial connectedness of major financial institutions is not complete without an analysis of directional connectedness across financial institutions. Calculation of variance decompositions requires orthogonal innovations, whereas the VAR innovations are generally correlated. Identification schemes such as that based on Cholesky factorization achieve orthogonality, but the variance decompositions then depend on the ordering of the variables. As a result, it is not possible to use the variance decompositions from the Cholesky factor orthogonalization to study the direction of connectedness. With this understanding, Diebold and Yilmaz (2012) propose to circumvent this problem by exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which produces variance decompositions invariant to ordering. Instead of attempting to orthogonalize shocks, the generalized approach allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors. As the shocks to each variable are not orthogonalized, the sum of contributions to the variance of forecast error (that is, the row sum of the elements of the variance decomposition table) is not necessarily equal to one.

Using the VAR framework introduced above, we define *own variance shares* to be the fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_i, for $i = 1,2,..,N$, and *cross variance shares*, or *connectedness*, to be the fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_j, for $i, j = 1,2,..,N$, such that $i \neq j$.

The generalized impulse response and variance decomposition analyses also rely on the MA representation of the N-variable VAR(p) equation above. Pesaran and Shin (1998) show that when the error term ε_t has a multivariate normal distribution, the h-step generalized impulse response function scaled by the variance of the variable is given by:

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \Sigma \mathbf{e_j}, \qquad h = 0, 1, 2, ... \tag{2}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and $\mathbf{e}_i$ is the selection vector with one as the i^{th} element and zeros otherwise. Variable j's contribution to variable i's H-step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, for $H = 1,2,...$, is defined as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{3}$$

As explained above, the sum of the elements of each row of the variance decomposition table is not necessarily equal to 1: $\sum_{j=1}^{n} \theta_{ij}^{g}(H) \neq 1$. In order to use the information available in the variance decomposition matrix to calculate the connectedness index, Diebold and Yilmaz (2012) normalize each entry of the variance decomposition matrix (equation 3) by the row sum as[1]:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{4}$$

Now, by construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. Using the normalized entries of the generalized variance decomposition matrix (equation 4), Diebold and Yilmaz (2012) construct the total connectedness index as:

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \tag{5}$$

Next considering directional connectedness, Diebold and Yilmaz (2012) define gross directional connectedness received by bank *i* from all other banks *j* as:

$$C_{i \leftarrow \bullet} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{6}$$

In similar fashion, directional volatility connectedness transmitted by bank *i* to all other banks *j* is measured as:

$$C_{\bullet \leftarrow i} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{7}$$

One can think of the set of directional connectedness as providing a decomposition of total connectedness into those transmitted by each bank in the sample. Obviously, once the financial shocks transmitted and received by bank *i* are calculated, the difference between the two will result in a measure of the net directional connectedness transmitted from bank *i* to all other banks as:

$$C_i(H) = C_{\bullet \leftarrow i}(H) - C_{i \leftarrow \bullet}(H) \tag{8}$$

The net directional connectedness index (equation 8) provides information about how much each bank's stock return volatility contributes in net terms to other banks' stock return volatilities.

Diebold and Yilmaz (2014) showed that the connectedness framework was closely linked with the modern network theory. To start with, they showed that the total connectedness measure corresponds to the mean degree of a weighted, directed network. They also showed that the connectedness framework was closely linked to the modern measures of systemic risk. For example, the from-

1. Alternatively, one can normalize the elements of the variance decomposition matrix with the column sum of these elements and compare the resulting total connectedness index with the one obtained from the normalization with the row sum.

connectedness degree measures exposures of individual banks to systemic shocks from the network, in a way very much similar to the marginal expected shortfall of these banks (Acharya et al. (2010)). The to-connectedness degree, on the other hand, measures the contribution of individual banks to systemic network events, in a fashion very similar to CoVaR of the bank (Adrian and Brunnermeier (2016)).

3. Bank Stock Return Volatilities, 2004-2016

Thus far, we have reviewed the tools for connectedness measurement. Next, we will use those tools to characterize the evolution of volatility connectedness among major SEACEN region banks in the age of financial crises.

Financial institutions are connected directly through counter-party linkages associated with positions in various assets, through contractual obligations associated with services provided to clients and other institutions, and through deals recorded in their balance sheets. High-frequency analysis of financial institution connectedness, therefore, might seem to require high-frequency balance sheet and related information, which is generally unavailable.

Fortunately, however, the data on stock returns and return volatilities are available, which reflect forward-looking assessments of many thousands of strategic and often privately informed agents as regards precisely the relevant sorts of connections. We, therefore, use the available stock returns and return volatilities data to measure connectedness and its evolution. It is important to note that we remain agnostic as to how connectedness arises; rather, we take it as given and seek to measure it correctly for a wide range of possible underlying causal structures.

In this report, we study *volatility* connectedness, for at least two reasons. First, if volatility tracks investor fear (e.g., the VIX is often touted as an “investor fear gauge”), then volatility connectedness is the “fear connectedness” expressed by market participants as they trade. We are interested in the level, variation, paths, patterns and clustering in precisely that fear connectedness. Second, volatility connectedness is the main focus because we are particularly interested in crises, and volatility is very often crisis-sensitive in practice.

Volatility is latent and hence must be estimated. There are many ways to estimate volatility, such as GARCH type observation based models, stochastic volatility models, realized volatility and implied volatility. In this paper, we use range estimate of the daily volatility, following the method developed by Garman and Klass (1980). Range volatility has received considerable interest in recent years (see Alizadeh et al. (2002)). For a given bank on a given day, we construct the daily range volatility estimate using the natural logarithms of daily high (h), low (l), opening (o) and closing (c) prices as proposed by Garman and Klass (1980):

$$\tilde{\sigma}_{gk}^{2} = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2$$

Volatilities tend to be strongly serially correlated – much more so than returns, particularly when observed at relatively high frequency. We capture that serial correlation using vector-autoregressive approximating models, as described earlier. Volatilities also tend to be distributed asymmetrically, with a right skew, and approximate normality is often obtained by taking natural logarithms. Hence, we work throughout with log volatilities. This is helpful not only generally, as normality-inducing transformations take us into familiar territory, but also specifically as we use generalized variance decompositions (Koop et al. (1996), Pesaran and Shin (1998)), which invoke normality.

In our analysis, we include stock return volatilities for 63 major SEACEN region banks. The sample covers the period from January 2004 to December 2016. Tables 1 and 2 present the list of the SEACEN region commercial banks, along with the symbols we use to identify them in network graphs, stock market capitalization and total assets as of the end of the sample (December 31, 2016). These are the largest banks such that stocks of the majority of the banks covered in our sample are included in the major stock market indices in their respective economies.

4. Estimation of the Vector Autoregression

4.1 Selecting and Shrinking the Approximating Model

As we have already noted above, 63 banks from the SEACEN region are included in the analysis. Increasing the number of variables in a VAR setting, quickly consumes degrees of freedom and we need a longer estimation period to increase the number of observations. Lengthening the estimation period, on the other hand, precludes the correct estimation of the change in the coefficients over time. In order to conduct the analysis of connectedness among a larger number of banks, we use selection and shrinkage methods. We are using a hybrid of shrinkage (Informative-prior Bayesian analyses, ridge regression) and selection (Information Criteria) methods, which are based on the lasso estimator.

The elastic net estimator (Zou and Hastie, 2005) solves:

$$\beta Enet = \arg\min^{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} \left(\alpha|\beta_i| + (1-\alpha)\beta_i^2 \right) \right)$$

Elastic net is a hybrid of lasso and Ridge regression; that is, it combines a lasso L_1 penalty and a ridge L_2 penalty. There are two tuning parameters, λ and $\alpha \in [0,1]$. Obviously, elastic net is lasso when $\alpha = 1$ and ridge when $\alpha = 0$. While lasso may select only one of the strongly correlated predictors and drop the others, elastic net makes sure that they are in or out of the model together.

Table 1
SEACEN Region Financial Institution Detail (bn.US$)

Institution	Symbol	Market Cap.		Total Assets	
		2004	2016	2004	2016
Total		**265.75**	**827.5**	**2037.2**	**8168.2**
China	**CHN**	**15.7**	**176.3**	**216.5**	**2627.9**
China Merchants Bank	chn.cmbc	6.91	63.06	70.87	843.33
Shanghai Pudong Dev. Bank	chn.spdb	3.31	50.47	55.04	777.00
China Minsheng Banking Corp	chn.cmnh	3.41	46.06	53.81	696.34
Hua Xia Bank	chn.hxbc	2.11	16.70	36.77	311.24
Hong Kong	**HKG**	**53.34**	**86.04**	**209.6**	**605.99**
BOC Hong Kong Holdings	hkg.bchk	20.20	37.84	102.51	305.53
Hang Seng Bank	hkg.hsb	26.57	35.58	70.37	172.18
Bank of East Asia	hkg.boea	4.64	10.35	27.07	100.82
Dah Sing Financial Holdings	hkg.dsfh	1.93	2.27	9.65	27.46
India	**IND**	**33.64**	**186.31**	**338.56**	**1323.99**
State Bank of India	ind.sbi	7.94	28.59	144.07	448.44
ICICI Bank	ind.icbk	6.31	21.87	40.90	138.68
HDFC Bank	ind.hdbk	3.44	45.36	11.79	110.23
Punjab National Bank	ind.pnbk	2.49	3.62	29.36	107.59
Bank of Baroda	ind.bob	1.63	5.20	22.32	104.33
Canara Bank	ind.cnbk	2.02	2.10	25.47	85.09
Axis Bank	ind.axbk	1.00	15.84	8.65	80.31
Union Bank of India	ind.unbk	1.16	1.25	16.60	61.49
Housing Development Fin. Corp.	ind.hdfc	4.37	29.46	10.32	60.03
IDBI Bank	ind.idbi	2.00	2.10	19.02	56.49
Kotak Mahindra Bank	ind.ktkm	0.79	19.48	2.62	36.35
Indusind Bank	ind.inbk	0.41	9.75	3.58	21.14
Federal Bank	ind.fed	0.08	1.69	3.86	13.82
Indonesia	**IDN**	**19.07**	**82.22**	**81.39**	**284.07**
Bank Mandiri	idn.bmri	4.12	19.86	26.77	74.74
Bank Rakyat Indonesia	idn.bbri	3.62	21.18	11.55	71.41
Bank Central Asia	idn.bbca	3.89	28.09	16.09	50.60
Bank Negara Indonesia	idn.bbni	2.37	7.58	14.73	40.81
Bank CIMB Niaga	idn.bnga	0.38	1.56	3.32	18.17
Bank Pan Indonesia	idn.pnbn	0.72	1.33	2.58	14.95
Bank Danamon Indonesia	idn.bdmn	3.97	2.62	6.35	13.39

Table 2
SEACEN Region Financial Institution Detail (bn.US$, cont'd)

Institution	Symbol	Market Cap.		Total Assets	
		2004	2016	2004	2016
Malaysia	**MYS**	**28.18**	**64.7**	**179.79**	**595.41**
Malayan Banking	mys.mbbm	11.33	18.64	49.05	172.96
CIMB Group Holdings	mys.cimb	3.33	8.92	29.58	117.52
Public Bank	mys.pubm	6.27	17.08	24.30	93.36
RHB Capital	mys.rhbc	1.12	4.21	21.62	57.81
Hong Leong Financial Group	mys.hlcb	1.22	3.64	14.62	50.82
Hong Leong Bank	mys.hlbb	2.29	6.53	13.54	45.68
AMMB Holdings	mys.ammb	1.61	2.90	15.83	30.11
BIMB Holdings	mys.bimb	0.25	1.50	5.12	13.89
Alliance Financial Group	mys.alfg	0.76	1.28	6.13	13.26
Philippines	**PHL**	**7.24**	**19.97**	**20.94**	**113.89**
BDO Unibank	phl.bdo	1.20	8.26	3.20	45.64
Metropolitan Bank and Trust	phl.mbt	2.35	4.65	9.36	35.39
Bank of the Philippine Islands	phl.bpi	3.69	7.06	8.38	32.86
Singapore	**SGP**	**38.59**	**79.56**	**263.64**	**871.69**
DBS Group Holdings	sgp.dbsm	14.72	30.52	107.60	341.69
Oversea-Chinese Banking Corp.	sgp.ocbc	10.89	25.84	73.43	289.36
United Overseas Bank	sgp.uobh	12.98	23.20	82.61	240.64
South Korea	**KOR**	**10.06**	**23.7**	**215.27**	**592.12**
Shinhan Financial Group	kor.sfgc	7.22	17.80	141.85	362.41
Industrial Bank of Korea	kor.ibok	2.84	5.90	73.42	229.71
Chinese Taipei	**TWN**	**43.42**	**53.38**	**366.48**	**719.93**
CTBC Financial Holding	twn.ctbc	6.90	10.61	45.02	154.87
Mega Financial Holding	twn.mfhc	7.84	9.64	66.82	105.46
First Financial Holding	twn.ffhc	4.76	6.38	47.34	80.85
Hua Nan Financial Holdings	twn.hnfh	4.76	5.30	50.12	80.80
Chang Hwa Commercial Bank	twn.chcb	3.33	4.74	41.37	61.99
E.Sun Financial Holding	twn.efhc	2.44	4.99	15.70	58.90
Sinopac Financial Holdings	twn.sfhc	2.35	3.00	32.16	52.12
Taishin Financial Holding	twn.tfhc	4.14	3.48	27.25	48.56
Taiwan Business Bank	twn.tbb	1.49	1.50	32.50	47.25
China Development Financial Hldg	twn.cdfh	5.41	3.74	8.20	29.13
Thailand	**THA**	**16.47**	**55.33**	**145.02**	**433.22**
Bangkok Bank	tha.bbl	5.09	8.49	36.23	83.16
Siam Commercial Bank	tha.scb	2.13	14.46	19.69	81.16
Kasikornbank	tha.kbank	3.18	11.84	21.23	79.30
Krung Thai Bank	tha.ktb	2.58	6.89	29.57	77.77
Bank of Ayudhya	tha.bay	0.88	8.21	14.81	52.86
Thanachart Capital	tha.tcap	0.92	1.48	4.76	28.74
TMB Bank	tha.tmb	1.28	2.57	17.25	23.43
Kiatnakin Bank	tha.kkp	0.41	1.39	1.48	6.80

4.1.1 Implications of Shrinkage and Selection

Adaptive elastic net does not directly minimize the sum of squares, thus the estimated coefficients are generally biased. Although the bias is not very large when one does not work with very high dimensional models, it still requires consideration. There are important points, however, that justify overlooking the bias in our analyses.

Firstly, the adaptive elastic net applies the shrinkage mainly on small coefficients, therefore, underestimates the smaller ties between banks. However, since we are using variance decompositions, we utilize indirect links between these two bank stock return volatilities over a ten-day period. This mechanism is intuitively appealing since we know that the effects of a shock on one bank stock is generally propagated to distant (both geographically and economically) banks mainly through intermediate neighbors. The same reasoning can be applied to the selection stage; although many coefficients in our VAR are zero, we still measure (more realistic) non-zero edges using variance decomposition. Also, the variance decompositions are always positive regardless of the signs of the coefficients in the VAR. We see it as an advantage, since our aim is not just to detect the co-movements; we aim to see which banks are more important in the determination of stock return volatility of other banks.

Secondly, the higher coefficients are scaled down according to their sizes, therefore, the relative importance of domestic and global factors[2] does not necessarily vary. In addition, we still expect to see the bank with higher coefficient as the one with the thicker edge on our network graph.

Thirdly, we need to inquire whether adaptive elastic net can be used on VAR estimation as it is used on simple linear regressions. Furman (Furman (2014a), Furman (2014b)) shows that the elastic net does not preclude the efficient equation by equation estimation of VAR. Moreover, it also leads to accurate forecasts and the resulting impulse response functions are valid.

4.2 Graphical Display

This report aims to present network graphs with as many as 63 nodes, which by implication means that there are as many as $3969 = 63^2$ edges. Presenting the complete network with 3969 edges on a graph would not be very informative and would require a high level of attention to identify patterns in the network structure. Therefore, in the majority of the graph, we will present only 25% of the existing links by removing the weakest links in the graphs. In all graphs we compare, we will make sure that they all have the 25 percent of the edges visible. We use node size, node color, edge thickness, edge arrow size and edge color to convey extra and hard-to-spot information about the graph together with the node location.

In order to prepare the network graphs, we use Gephi, an open-source software for visualizing and analyzing large network graphs. The networks we are focusing on are complete, weighted, directed networks. The networks are complete, since the object of interest is the 10-day ahead forecast errors in determining effects. It would be naive to assume that a shock to one of the bank stocks would not have an effect on other bank stocks in a period of 10 days. We need to work with directed networks since the effect of one bank stock to another is not necessarily the same with the effect on the other direction. Finally, there is a need to use weighted networks, since the magnitudes of effects differ substantially across banks. Using simple binary networks would hide valuable information about the systemic structure of the sovereigns. Gephi is the best publicly available software that one can use to plot large network graphs that satisfy all these properties.

2. These are generated through variance decompositions and sum up to 100%.

Node Size Indicates Total Assets or Market Capitalization
In the full sample and rolling windows analyses node sizes are determined by bank total assets as of the end of 2016.

Node Color Indicates Total Directional Connectedness "To Others"
The node color indicates total directional connectedness "to others," ranging from 3DFA02 (bright green), to E6DF22 (luminous vivid yellow), to CF9C5B (whiskey sour), to FC1C0D (bright red), to B81113 (dark red; close to scarlet). That is, a bank stock that is less influential in the major European bank sample will be colored close to bright green while a highly influential sovereign will be colored closer to dark red. The color thresholds (presented in Table 3) are determined by taking the 30, 60, 80, 90 and 95 percentiles of the 'to' connectedness measures of all banks obtained from all 150-day rolling-windows estimations for the 2004-2016 sample, throughout the rolling-sample dynamic connectedness analysis. Therefore, node colors are comparable across network graphs presented in the rest of the paper.

Table 3
Total Directional Connectedness Thresholds for Node Colors

Percentile	30%	60%	80%	90%	95%
Threshold Value	39.1	57.8	75.2	87.5	97.6

Figure 1
Color Spectrum

Node Location Indicates Strength of Average Pairwise Directional Connectedness
The node locations are determined using the ForceAtlas2 algorithm of Jacomy et al. (2014) as implemented in Gephi. The algorithm finds a steady state in which repelling and attracting forces exactly balance, where (1) nodes repel each other, but (2) edges attract the nodes they connect according to average of the pairwise directional connectedness measures, "to" and "from." The steady state node locations depend on initial node locations and hence are not unique. However, this shortcoming is irrelevant, as we are interested in relative - not absolute - node locations in equilibrium. The relative positions of nodes are similar across equilibria.

Edge Thickness Indicates Average Pairwise Directional Connectedness
Edge color is lighter for the weakest links and same for all the others. Since we represent average pairwise directional connectedness with edge thickness, we use the edge color just for the sake of clearer visuals.

Edge Arrow Sizes Indicate Pairwise Directional Connectedness "To" and "From"
Since the full set of edge arrow sizes reveals the full set of pairwise directional connectedness measures - from which all else can be derived (with the exception of credit rating) - the various additional devices employed (node color, node location, and edge thickness) are in principle redundant and therefore, unnecessary. In practice, however, they are helpful for examining large networks in which, for example, the thousands of arrows can be quite impossible to see. They are, therefore, invaluable

supplements to the examination of "edge arrows" alone. Finally, the caption of each network plot includes two pieces of additional information. First, it includes the total volatility connectedness index obtained for the corresponding rolling sample window. Second is the scale of the network plot. As the volatility connectedness increases and the network becomes tighter, the edges will be significant and attract nodes, making the network size small. As a result, we increase the scale of the network plot by a factor of 2 to 8. Therefore, the higher the scale parameter the tighter is the network.

5. Static (Full-Sample, Unconditional) Analysis

In this section, we analyze the full-sample, static, unconditional volatility connectedness among the major SEACEN region banks. The full-sample static volatility connectedness (network) plot is presented in Figure 2. The nodes represent 63 bank stocks included in our analysis. As already noted above, the size of each node indicates the total asset size of the corresponding bank as of the end of 2016 (see Tables 1 and 2).

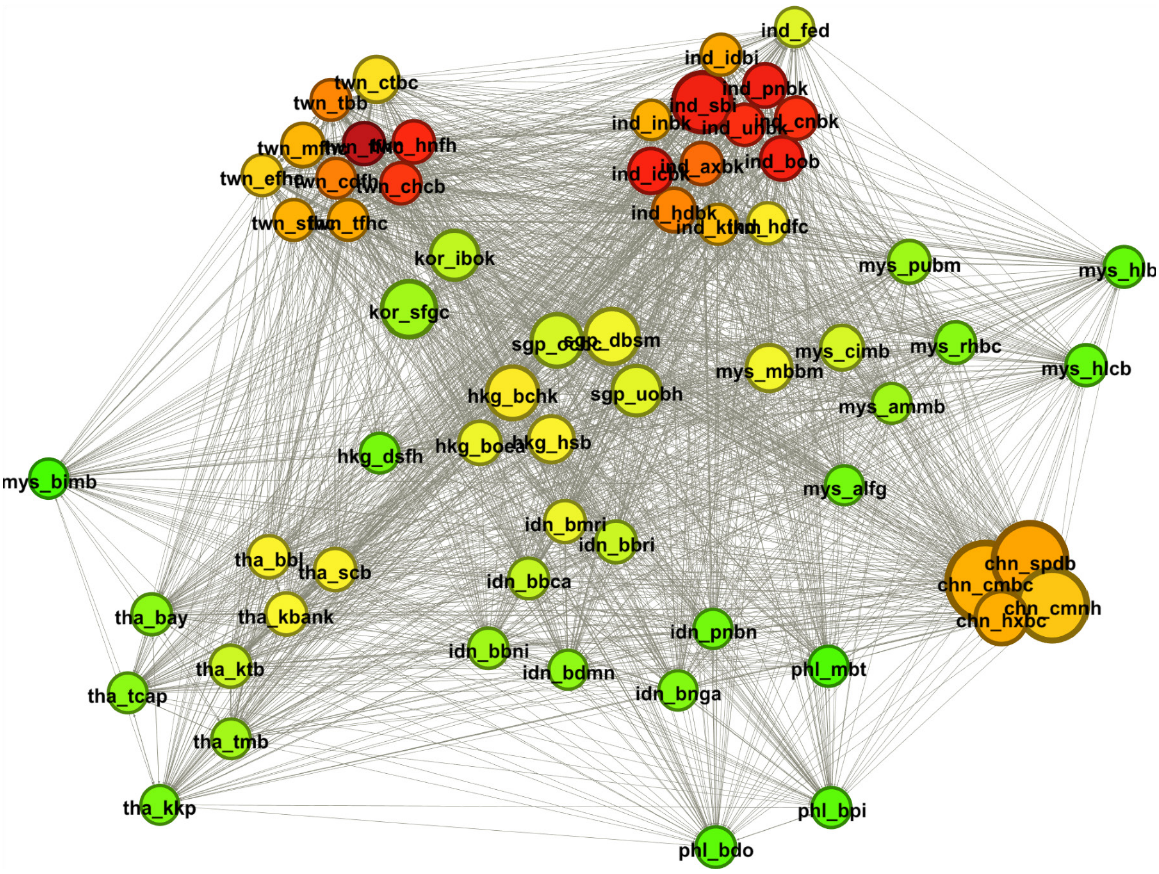
The color of each node (in decreasing order from crimson red to red, orange, yellow, green and bright-green) indicates the size of the directional volatility connectedness from the particular bank stock "to" others.

The location of the node also provides information about the directional connectedness measures for each bank. The higher the total directional connectedness of the bank stock "to" others, the closer it is located to the center of the connectedness plot. In the full sample, the bank nodes are spread out and stay quite distant from each other. The connectedness index for the full sample is 48.5%, which is relatively low, for example, compared to a connectedness index of 70.6% for 38 European banks over the period from 1999 to 2015.

Consistent with the low level of connectedness, there is only one bank that had high connectedness to others (with a node color of crimson red). It is a Chinese Taipei bank, namely, First Financial Holding Bank. It was followed by two Chinese Taipei and several Indian banks.

As can be seen from their red- or orange-colored nodes for the majority of them, Indian banks tend to generate high volatility connectedness to other economies in the full sample. This, however, does not mean that Indian banks generated high volatility connectedness to others always throughout the 2004-2016 sample. It rather reflects the problems facing the Indian banks lately especially after the demonetization decision of the Indian government on November 2016, which we will discuss in detail in Section 6.2.

Figure 2
SEACEN Region Bank Volatility Connectedness – 63 Banks, (Index=48.5%)



Based on pairwise directional volatility connectedness over the full-sample, from January 5, 2004 to December 31, 2016.

It is not unexpected to have the Indian banks to have higher "to" connectedness, as they outnumber banks of other economies. There are 13 Indian banks and they, on average, tend to be large. The total asset size of 13 Indian banks reaches US$1.3 trillion.

In terms of connectedness, Indian banks are followed by Chinese Taipei banks (nodes with crimson red, red and orange colors) and Chinese banks (all having orange-colored nodes). The total asset size of 10 Chinese Taipei banks was US$719 billion as of the end of 2016.

There are only four Chinese banks in our sample. However, the four Chinese banks are big. As of the end of 2016, they had a total asset size of US$2.6 trillion in 2016, making up close to one-third of the total assets of all banks included in our sample from the region. Even though, they are among the biggest in terms of asset size, the Chinese banks are not as tightly connected as Indian and/or Chinese Taipei banks to banks of other economies.

Banks from Singapore, Hong Kong and South Korea are located at the center of the static network graph. Yet, they are not the main generators of volatility connectedness to others. Looking at the yellow- or green-colored nodes, we can conclude that these banks have indeed low to connectedness measures. They are likely to receive high volatility connectedness from other banks in their vicinity.

The two Korean banks are located very close to Chinese Taipei banks. When we turn to Figure 3(c) it becomes clear that First Financial Holding Bank of Chinese Taipei (twn.ffhc) generates substantial volatility connectedness to both of the Korean banks in the static full sample so that we can observe these edges among the top 10 percent edges of the static connectedness network. Hua Nan Financial Holdings is the other Chinese Taipei bank that generates significant connectedness to the Industrial Bank of Korea in the full sample analysis.

In Figure 3, we present the volatility connectedness network after trimming the weakest edges; first, trimming the weakest 50% of edges, then trimming the weakest 75% of edges and finally trimming the weakest 90% of edges. In addition, Figure 3 also presents the volatility connectedness network when the individual bank nodes are grouped in terms of modularity.[3]

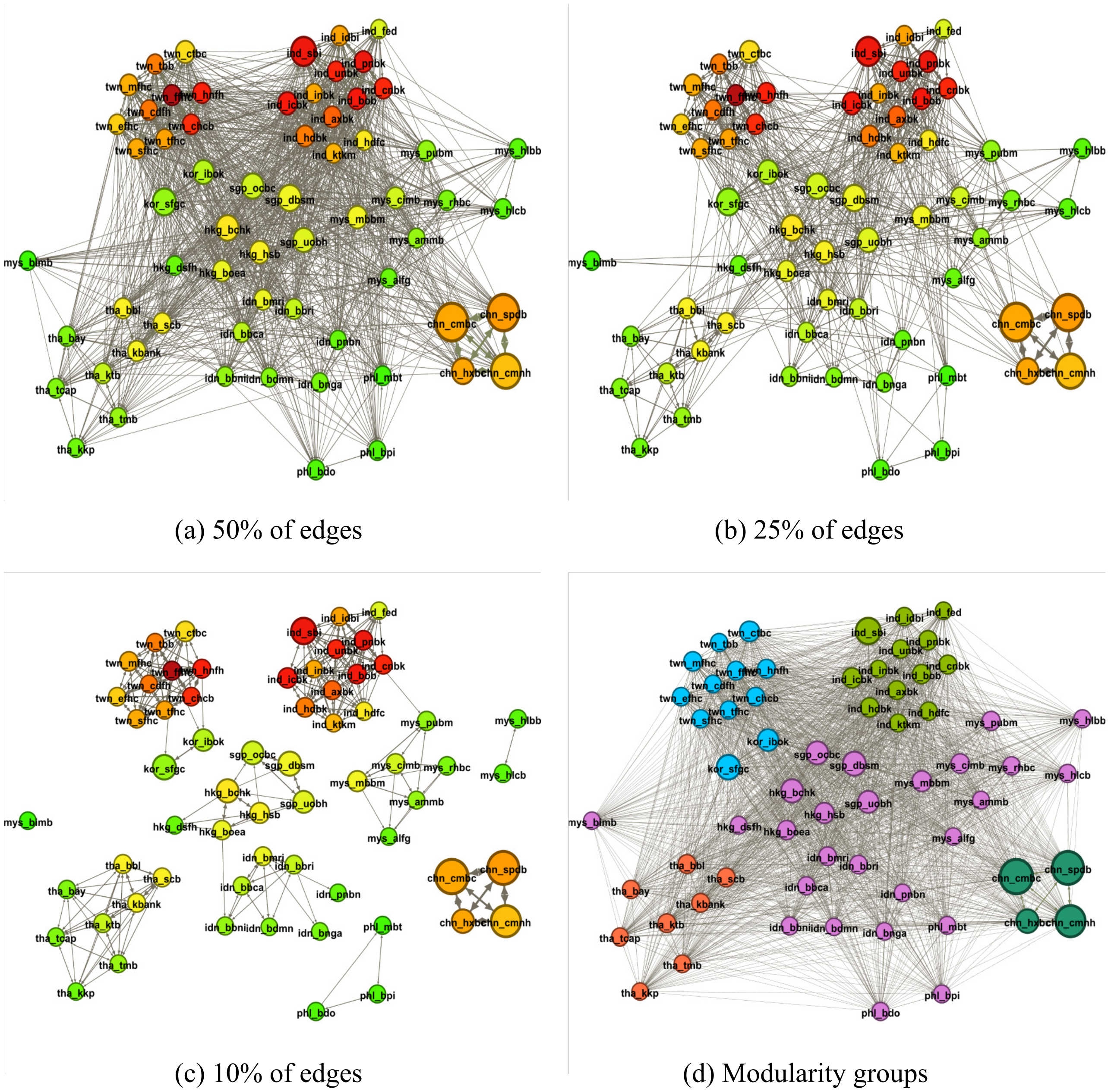
The full-sample static volatility connectedness network appears to cluster on the basis of the economy of origin. Yet, as can be seen from Figure 3(d), while Indian, Chinese and Thai banks form economy-level clusters, banks from other five economies (namely, Hong Kong, Indonesia, Malaysia, the Philippines, and Singapore) form one big modular group as indicated by their purple-colored nodes. Actually, if we were to drop Hong Kong from this group and add Thailand, we would have the ASEAN-5 economies at hand. Therefore, in the full sample static analysis, we observe at least four of the ASEAN-5 economies seem to spread volatility shocks to each other more than to economies outside the group. Finally, in the modularity analysis, it appears that two South Korean banks join Chinese Taipei banks to form a two-economy cluster of bank stock return volatility connectedness (with blue-colored nodes).

Even though they are one of the crowded bank groups, Malaysian banks do not form a single cluster. Eight of nine Malaysian banks are located on the right side of the graph in Figure 2, while one Malaysian bank, BIMB holdings, is located on the left side of the graph. When we look at the network after dropping less important edges, it appears that BIMB has close links to Thai banks, as well as two of the Malaysian banks. However, it turns out that its links with Thai banks and other Malaysian banks are not as strong as we observe in the case of other banks. When we present only the top 10% of all edges, Malaysian BIMB bank turns out to have no important link with another bank among our sample of SEACEN banks (Figure 3(c)).

Finally, with a value of 48.5%, the total connectedness among 63 bank stocks is lower than the 65% value of total connectedness index obtained for 38 major European banks (see Yilmaz (2015)). Despite that, it is still higher than the connectedness among different asset classes, or among international stock markets (see Diebold and Yilmaz (2015)). Given the large number of stocks included in the analysis, there is a high degree of connectedness for the full-sample. As we will see later in analyzing the dynamic behavior of the total connectedness, there is always a high degree of connectedness even during tranquil times.

3. In order to make sure that bank codes are readable, we specifically prevented the overlap of nodes in these smaller graphs. That is why the graphs presented in 3 may look slightly different from Figure 2, even though they are actually the same graphs with the most important edges.

Figure 3
Connectedness Network - After Trimming and Modularity Groups (Jan. 2004-Dec. 2016)



(a) 50% of edges

(b) 25% of edges

(c) 10% of edges

(d) Modularity groups

So far, we have analyzed the volatility connectedness of the SEACEN region banks in isolation. That is obviously not a very realistic assumption. SEACEN region banks are likely to be affected from developments in the global financial system. In particular, shocks to GSIBs can spread to the banks in the region. In addition, Japan and Australia are the two countries in the region with sizeable banking systems that can transfer volatility shocks to SEACEN region banks. Taking this fact into account, we add 22 GSIBs from the US (10) and Europe (12), as well as major Japanese (8) and Australian (6) banks (for the list of these banks see Table 4). At this stage, it is important to note that three (Mitsubishi UFG FG, Mizuho FG and Sumitomo Mitsui FG) of the eight Japanese banks are classified by the Financial Stability Board, recently established international banking watchdog, as GSIBs in 2016.[4] When we add the stock return volatilities of these 36 banks, the resulting static bank network is quite different from the one for the SEACEN banks only. As expected, the majority of GSIBs are the banks with the highest connectedness "to others". Three Japanese GSIBs generate moderate connectedness "to others" as indicated by their orange node colors.

With the expansion of the sample to include GSIBs, as well as major Japanese and Australian banks, the structure of the SEACEN network changed significantly. First, as expected the Indian and Chinese Taipei banks are no longer the top generators of volatility connectedness to others. They only come after GSIBs and Japanese banks. As a result, node colors of some Indian and Chinese Taipei banks turned from crimson red or red into orange or yellow. Among the SEACEN region banks, Indian and Chinese Taipei banks are still generating more connectedness to others even after the inclusion of GSIBs, Japanese and Australian banks. Next, Indian and Chinese Taipei banks that were located close before, are now located further away from each other. Chinese Taipei banks are now located closer to American and European GSIBs and Japanese banks, while Indian banks are located closer to banks of China, Malaysia, Indonesia and the Philippines. Banks from other economies of the region continue to have green colored nodes as before. Finally, as indicated by their yellow or green colored nodes, Australian banks tend to generate quite low connectedness to others. Indeed, in the network, they are located close to American and European GSIBs, from which they received high volatility connectedness.

The full-sample connectedness analysis provides a good characterization of "unconditional" aspects of the connectedness measures. However, it does not help us understand the connectedness *dynamics*. The appeal of the connectedness methodology lies with its use as a measure of how quickly return or volatility shocks spread across countries as well as within a country. This section presents the dynamic connectedness analysis which relies on rolling estimation windows. The dynamic connectedness analysis uses daily range volatilities for 63 SEACEN region bank stocks that were used in the static, unconditional, full-sample analysis.

The dynamic connectedness analysis starts with the total connectedness, and then moves to various levels of disaggregation (total directional and pairwise directional). Finally, a brief assessment of the robustness of the results to choices of tuning parameters and alternative identification methods will be included at the end of the section.

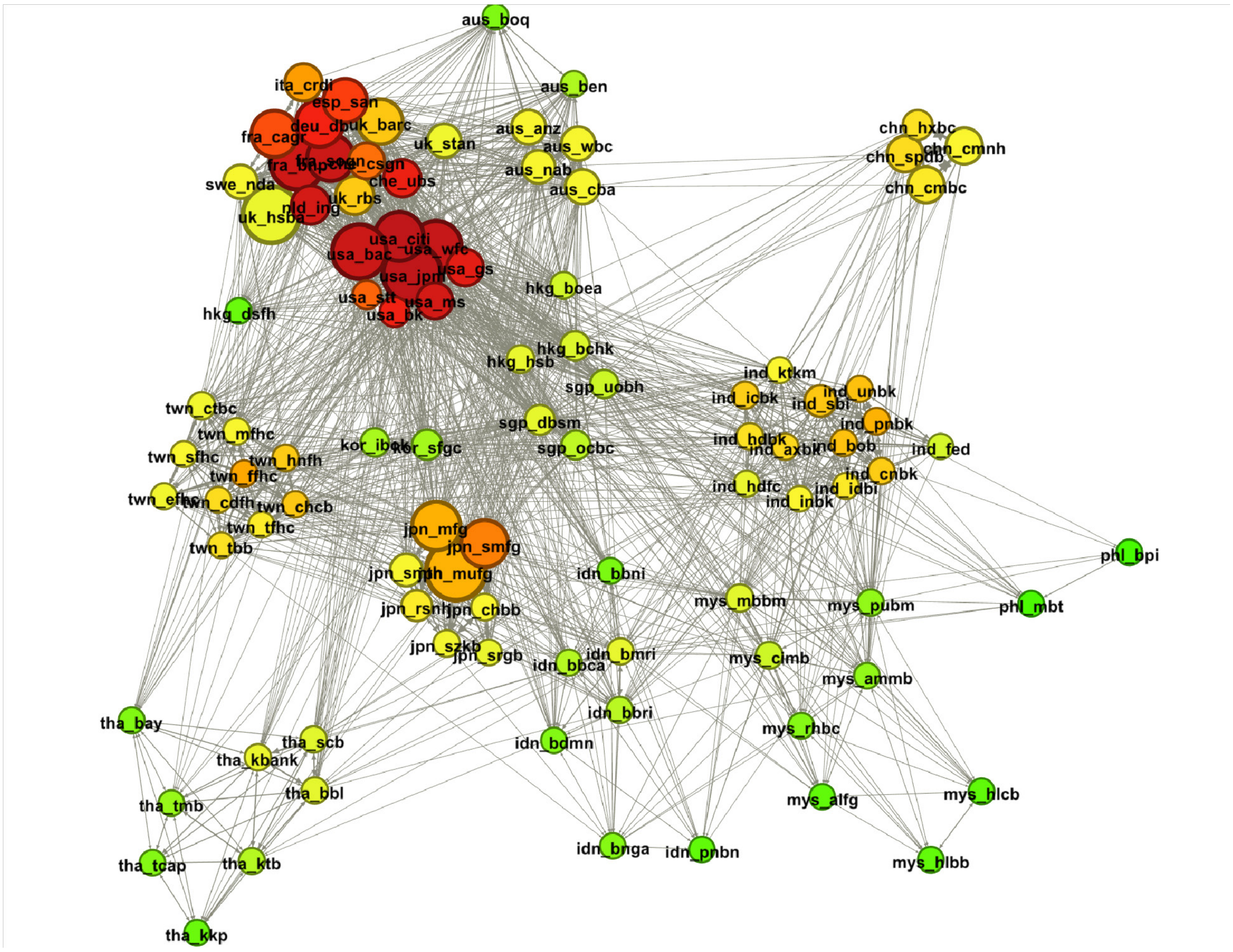
4. There are four Chinese banks in the GSIB list, but all of them are state owned with no shares traded in the stock exchange. For that reason, we cannot include them in our analysis.

Table 4
Details of GSIBs, and Major Banks of Australia & Japan (bn. US$)

Bucket	Institution	Sym.	Country	Assets	M. Cap
GSIB 4 (2.5%)	Citigroup	usa.citi	U.S.A.	1,792.08	169.36
	JP Morgan Chase	usa.jpm	U.S.A.	2,490.97	308.77
GSIB 3 (2.0%)	Bank of America	usa.bac	U.S.A.	2,187.70	223.32
	BNP Paribas	fra.bnp	France	2,183.51	79.34
	Deutsche Bank	deu.db	Germany	1,672.62	25.01
	HSBC	uk.hsba	U.K.	2,374.99	160.98
GSIB 2 (1.5%)	Barclays	uk.barc	U.K.	1,496.50	46.75
	Credit Suisse	che.csgn	Switzerland	805.50	29.86
	Goldman Sachs	usa.gs	U.S.A.	860.17	95.22
	Mitsubishi UFG FG	jpn.mufg	Japan	2,584.55	87.31
	Wells Fargo	usa.wfc	U.S.A.	1,930.12	276.78
GSIB 1 (1.0%)	Bank of New York Mellon	usa.bk	U.S.A.	333.47	50.10
	Groupe Credit Agricole	fra.cagr	France	1,602.43	35.25
	ING Bank	nld.ing	Netherlands	983.43	54.52
	Mizuho	jpn.mfg	Japan	1,748.81	45.57
	Morgan Stanley	usa.ms	U.S.A.	814.95	79.13
	Nordea	swe.nda	Sweden	647.24	45.05
	Royal Bank of Scotland	uk.rbs	U.K.	985.22	32.76
	Santander	esp.san	Spain	1,407.83	76.02
	Societe Generale	fra.sogn	France	1,621.45	39.69
	Standard Chartered	uk.stan	U.K.	646.69	26.88
	State Street	usa.stt	U.S.A.	242.70	29.98
	Sumitomo Mitsui FG	jpn.smfg	Japan	1,645.47	53.96
	UBS	che.ubs	Switzerland	918.66	60.35
	Unicredit Group	ita.crdi	Italy	903.63	17.77
Australia	Commonwealth B. of Australia	aus.cba	Australia	701.10	102.46
	Australia & N. Zealand B. G.	aus.anz	Australia	700.24	64.44
	Westpac Banking	aus.wbc	Australia	642.32	78.95
	National Australia Bank	aus.nab	Australia	595.19	59.09
	Bendigo and Adelaide Bank	aus.ben	Australia	51.19	4.33
	Bank of Queensland	aus.boq	Australia	38.21	3.32
Japan	Sumitomo Mitsui Trust Hldg	jpn.smth	Japan	547.08	13.97
	Resona Holdings	jpn.rsnh	Japan	409.88	11.92
	Chiba Bank	jpn.chbb	Japan	119.69	5.37
	Shizuoka Bank	jpn.szkb	Japan	101.96	5.59
	Suruga Bank	jpn.srgb	Japan	38.41	5.18

Notes: Financial Stability Board (www.fsb.org) allocates GSIBs to buckets corresponding to the higher capital buffers that they would be required to hold by national authorities in accordance with international standards.

Figure 4
SEACEN Bank Volatility Connectedness,
Incl GSIBs, Australian and Japanese Banks (DYCI=60.1%)



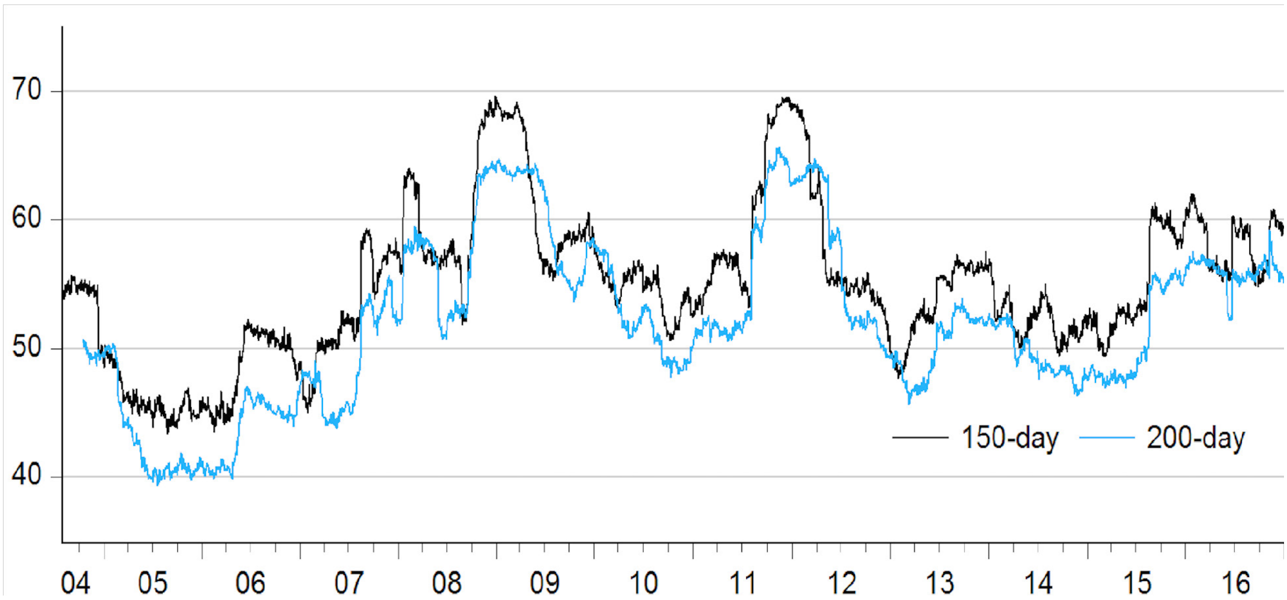
Based on pairwise directional volatility connectedness of 97 banks over the full sample, from January 5, 2004 to December 31, 2016.

6. Dynamic (Rolling-Sample, Conditional) Analysis

6.1 Total Connectedness

Figure 5 plots total volatility connectedness over 150-day and 200-day rolling-sample windows. It is preferable to work with a 150- and 200-day rather than a 100-day window size because the smaller the sample size, the more the total connectedness index fluctuates, which effectively makes it difficult to understand the impact of developments in financial markets as well as outside the financial markets. The 150-day and 200-day indices follow very similar patterns over time. In times of major volatility shocks, the 150-day index jumps more and reaches higher levels compared to the 200-day index as it reflects the impact of crisis events on the volatility connectedness better. As the 150-day sample window contains fewer days than the 200-day sample window, the influence of earlier events on the 150-day index would be lower than on the 200-day index. When there is an important volatility shock that spreads to the region's banks, the 150-day index is likely to reflect the impact of the new observation in the sample window much better than the 200-day index.

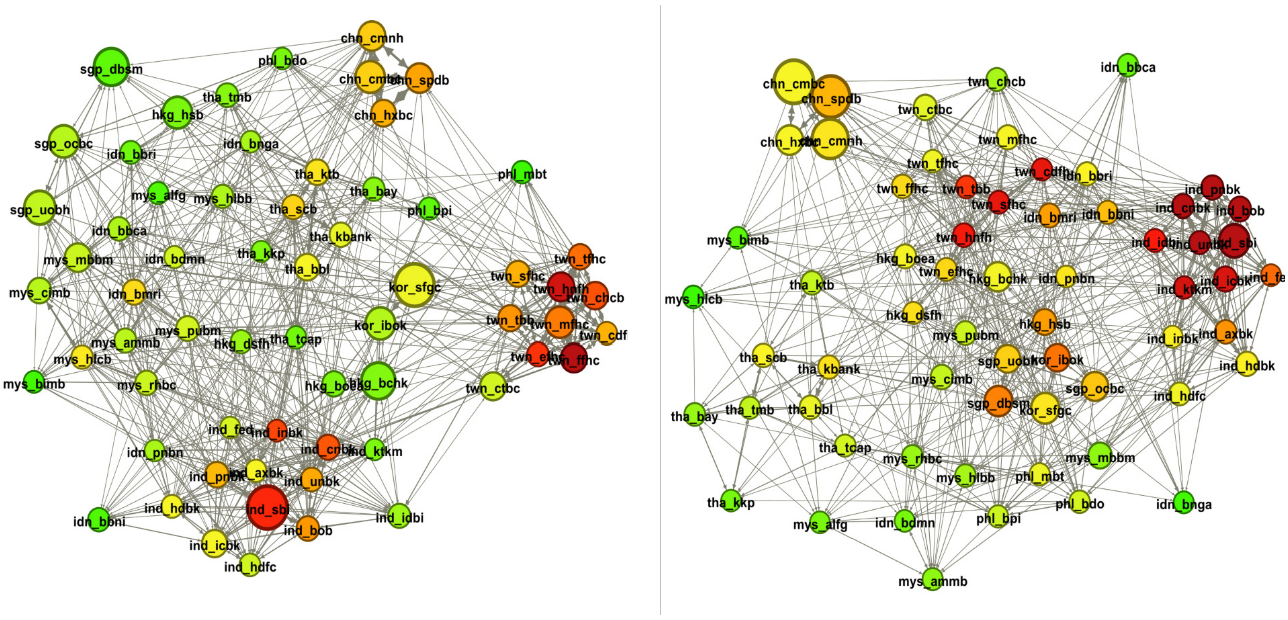
Figure 5
Dynamic Total Volatility Connectedness – 63 SEACEN Region Banks
(January 5, 2004 - December 31, 2016)



From a bird's-eye perspective, the total connectedness plot in Figure 5 has some revealing patterns. Total volatility connectedness among the SEACEN banks was high to begin with. The 150-day index started at a value of 53.8% in the first sub-sample window that ended on August 9, 2004 and fluctuated around 55% for some time. As the sub-sample window is rolled and the observation for May 17, 2004 is dropped out of the window, the connectedness index dropped to the 50.5% level first and later to 45% as the observations for August 2004 are left out of the sample window. It is interesting to note that even though one of the worst tsunamis wreaked havoc in the region on Sunday, December 26, 2004, killing more than 200,000 people, this did not have any impact on the volatility connectedness of the region's banks. This may be due to the fact that stock markets were closed on the day of the tsunami, yet it is observed that there is still no change in total volatility connectedness when the observations for December 27 are included in the sample window.[5]

5. In Karaca and Yilmaz (2016), we showed that the global insurance industry stocks suffered significantly when the earthquake and the ensuing tsunami hit the region, because insurance companies were expected to make compensations for insured individuals and property.

Figure 6
The Connectedness in the First and the Last Rolling Sub-sample Window



(a) Ends at Aug. 9, 2004 (index=53.8%) (b) Ends at Dec. 30, 2016 (index=59.3%)

The network connectedness for the SEACEN banks (with 75% of the edges trimmed) for the first rolling window is depicted in Figure 6(a). As can be seen clearly in Figure 6(a), the network connectedness of the regional banks does not create clear cut national clusters in the first rolling window considered. In the first sub-sample window, Chinese Taipei banks contribute more to total volatility connectedness than other economies' banks. At least four of the Chinese Taipei banks generated quite high connectedness to other banks in the SEACEN region. As indicated by their orange colors, the remaining Chinese Taipei banks were also generating high volatility connectedness to others. The fact that Chinese Taipei banks stand at a distance from others, on the other hand, indicate that a significant size of the directional connectedness of Chinese Taipei banks were spreading within the economy. [6] Among banks in other economies, three Indian banks that have red-colored nodes also generated volatility connectedness to others. Other banks of the region do not transmit high volatility shocks to others. As can be seen, banks from Singapore, Malaysia and Indonesia are scattered around each other without forming clear cut economy-level clusters.

Moving from the beginning to the end of the sample, we have a close look at the last rolling sub-sample window (which ends on December 30, 2016) in Figure 6(b). The total volatility connectedness in the last sub-sample window is only 5.5 percentage points higher than the one obtained in the first window. Despite significant increases in the index over the 12-year period, the soundness of the banking industry of the SEACEN region has not deteriorated over time. While at times volatility shocks to bank stock returns spread fast within the region, these did not have permanent effects on the region's bank stocks.

6. The dynamic net directional connectedness measures for each economy (see Figure 8) show that indeed the net connectedness of the Chinese Taipei banks as of August 2004 was higher than banks in other economies. In terms of net connectedness at the beginning of the sample, Chinese and Indian banks follow Chinese Taipei banks.

In the final sub-sample window, we again observe Indian and Chinese Taipei banks were generating connectedness to others. However, this time around, Indian banks are more influential than the Chinese Taipei banks, because they suffered substantially from the Modi government's decision to pull 500 and 1000 Rupee banknotes from circulation. Such a drastic decision reduced banks' profitability and their stock return volatilities reflected this fact since early November 2016. As a result of the high volatility connectedness generated by Indian banks, the total connectedness increased on November 9, 2016 by around 5 percentage points and stayed around 60% (see Figure 5).

The comparison of the network graphs in the first and the last sub-sample windows also reveals the relative sizes of bank assets at the beginning and the end of the sample as depicted. While in the first sample window Chinese banks were smaller relative to others, over time their asset sizes increased substantially surpassing banks from other countries in the SEACEN region in terms of asset size. While Chinese banks increased their relative asset size substantially, South Korean, Hong Kong, Singaporean and some Indian banks also increased their assets sizes from 2004 to 2016, yet in terms of asset size they are not larger than Chinese banks.

Both 150-day and 200-day indices recorded their first increases in May-June 2006 by approximately 7 percentage points. The increase in total volatility connectedness in May-June 2006 was due to the reaction of the stock markets to the Federal Open Market Committee's (FOMC) decision on May 10, 2006, to increase the federal funds rate target in May by 25 basis points as well as the announcement that there was room for another increase in its June meeting. The Fed's decision led to the unravelling of carry trade positions of many developed country investors in emerging market assets. Apparently, this led to an increase in volatility connectedness across the European as well as the American bank stocks. In a similar study of the European banks, we showed that the impact of the FOMC's unexpected May 2006 rate increase was much larger on European banks. The volatility index for the European banks increased by 20 percentage points in reaction (See, Yilmaz, 2015).

Following the jump in May-June 2006, the index moved to new highs as the tensions in the US financial system gradually led to a global financial crisis. It started in June 2007 and followed the stages of the global financial crisis, all the way to the end of 2009. The initial tremors of the subprime mortgage crisis were felt at the end of February 2007. At the end of February 2007, three mortgage originators filed for bankruptcy in the US. During those days, the Chinese stock market also recorded an unexpected drop. As a result of these events, and perhaps more importantly for the decline in Chinese stock market, the connectedness index went up approximately 5 percentage points at the end of February and the beginning of March 2007.

The first major development in the US financial crisis took place in the summer of 2007. First, two hedge funds of Bear Stearns collapsed in June. This development had its repercussions in Asian markets, so that the connectedness index increased from around 50% to 52.5% in mid-June. At the source of the problems of hedge funds were their heavy investments in mortgage-backed securities that were closely tied to the problems in the subprime mortgage markets. After the problems of Bear Stearns' owned hedge funds in June, in August BNP Paribas announced the liquidation of three of its hedge funds. This announcement led to a liquidity squeeze on both sides of the Atlantic, forcing US and European central banks to intervene. Asian markets could not be extricated from these major shocks at the center of the world financial system. The total volatility connectedness in the SEACEN region increased from 53% in June to 59% in August. However, the index did not stay at that level for a long time. As the observations for the early March are dropped from the rolling window sub-sample, the index went down by 5 percentage points. Had the impact of the liquidity crisis been sufficiently large, the index would not have gone down as the data points for early March were dropped from the sub-sample window.

In the fall of 2007, all major US banks started to announce major losses from their investments in derivatives related to the subprime real estate loans in the US. As a result, US banking stocks got the hit and spread part of these shocks to banks worldwide. Connectedness of the SEACEN region banks gradually increased from 54% in October to 58% in December. The gradual increase in the total connectedness index was followed by another jump which led the index to reach 63% as of the end of January 2008. The piling up of losses in major EU and US banks led to the intervention of their respective central banks, by way of lowering policy rates significantly. On January 22, 2008, the US Federal Open Market Committee held an unscheduled emergency meeting and reduced its Fed funds rate target from 4.25% to 3.50%. This decision was followed by a 50 basis point cut in its regular meeting on January 30, 2008. Yet, these decisions could not stop the bleeding in the US financial system. One of the weakest of the big US investment banks, Bear Stearns collapsed in March 2008, and it was sold to J.P. Morgan at a very big discount in an operation orchestrated by the New York Fed. As the takeover of Bear Stearns by J.P. Morgan was handled quite smoothly, it did not have any adverse effect on the global financial system and the SEACEN banks.

After the Bear Stearns takeover, the markets were calmer for several months. During this period, the SEACEN banks' volatility connectedness index declined back to pre-January level, and stayed at level until mid-August. As the observations for the January 2008 were dropped from the sub-sample window, the index went down to 52.5%. In the meantime, after a summer lull in the US financial markets, the American government could not find a suitor for the weakest US investment bank, Lehman Brothers. Lehman Brothers declared bankruptcy on September 15, 2008 and all hell broke out in financial markets worldwide. The Lehman Brothers' collapse had significant impact in the SEACEN region as well. SEACEN banks' volatility connectedness increased within ten days from 52.5% to 56.5%. However, this was not all. Immediately after the Lehman bankruptcy, it became apparent that AIG sold billions of dollars' worth of Credit Default Swaps (CDSs) insuring Lehman's debt. Once Lehman declared bankruptcy, it was AIG's liability to make tens of billions dollars of payments to Lehman's debt holders that purchased CDS contracts from AIG. From September 17 onwards, AIG started generating volatility connectedness worldwide. The Federal Reserve and US Treasury poured up to US$186 billion to save AIG. While these attempts prevented a complete meltdown of the US and therefore the global financial system, the genie had already gotten out of the bottle. The US financial crisis was transformed into a global financial crisis affecting all regions.

The SEACEN region's banks got their fair share of the volatility connectedness. The index increased sharply in October to reach 67% in early November. As the worries continued the index continued its upward move in an orderly fashion, reaching its maximum level at 69% by the end of 2008. The impact of the volatility shocks of the last quarter of 2008 kept the regional bank volatility connectedness high at around 68-69% points.

After the global financial crisis, total volatility connectedness recorded three small and short-lived upward cycles with rapid corrections. Even though the Greek debt crisis had shaken the European banks in mid-2010, the tremors of the Greek crisis did not reach the SEACEN region. Its impact was rather seen in a several percentage points increase in the index. Over this period, the total index fluctuated between 50% and 60%. However, the news about the troubles of the Portuguese and Spanish governments along with their banking systems, had a more significant impact on the connectedness. The index started to follow an upward path from 51% in October 2010 to 57% in May 2011. The SEACEN region bank volatility reacted more significantly to the downgrade of the US government's credit rating to AA by S&P in early August 2011. The index went up from 53% to 61% in early August first, followed by another jump from 63% to 69 in the last quarter of 2011 as the worries about the European economy continued.

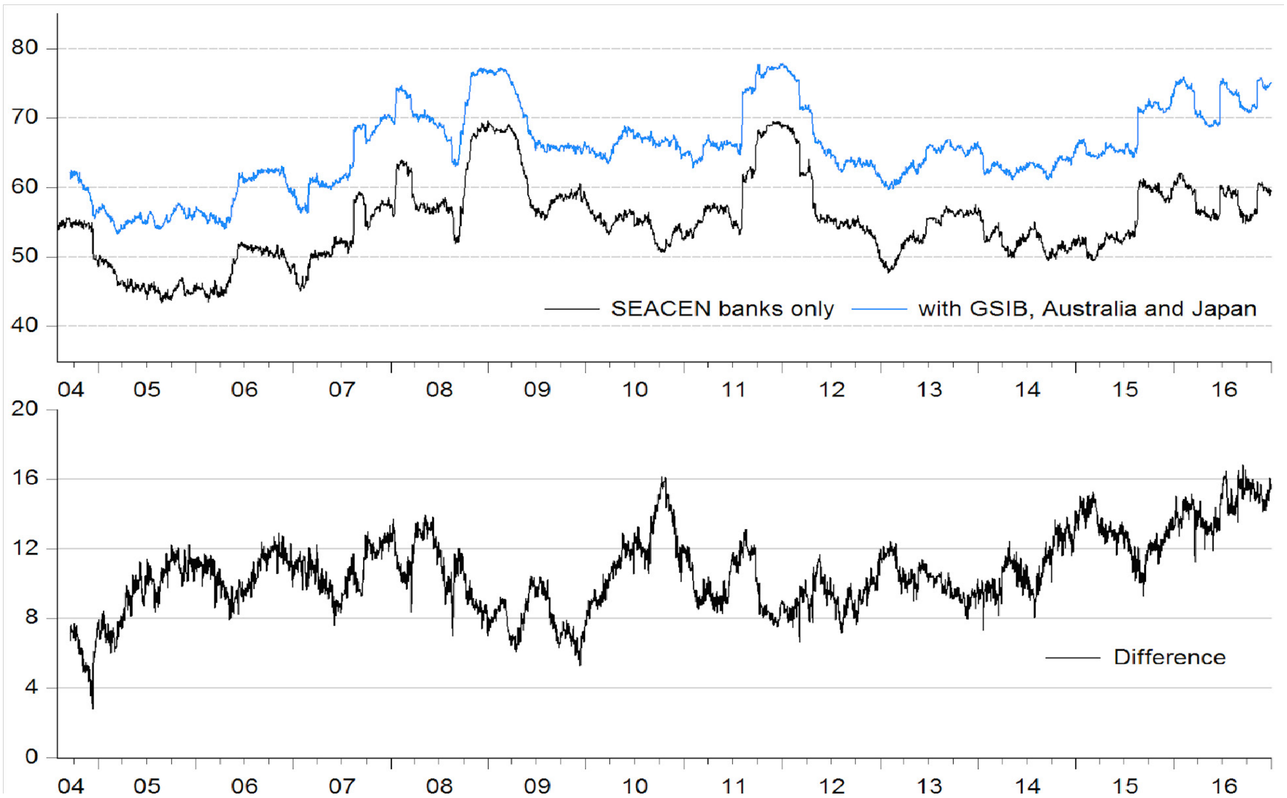
In July 2012, the European Central Bank (ECB) President Mario Draghi made a speech in London where he declared that the ECB was ready to do "whatever it takes" to protect the euro as the single European currency. Over the subsequent months, this speech had an enormous impact on the sovereign bond yields of two troubled countries, Italy and Spain. This had a worldwide calming effect, and as such is reflected in the total connectedness index of SEACEN bank stocks declining gradually to below 50% by early 2013. Then, Ben Bernanke's warnings about the eventual stopping of QE policies in the US in late 2013 and/or early 2014 led to capital outflows from many emerging market economies in late-May and June. The impact of this announcement on SEACEN bank stock volatility was around 5 percentage points.

After fluctuating in the 50-55% range for more than a year, the index went up in response to worries about the Chinese economy and financial market that started to show up in the summer of 2015. After a gradual increase that lasted for several months, the connectedness index moved up sharply in August 2015 by more than 8 percentage points.

The next jump in the index was on June 24, 2016, and was in reaction to the unexpected decision of the majority of British voters to support the motion for their country to leave the EU membership. There was a brief reaction to the Brexit decision in European and US markets, but it did not last very long. Similarly, the reaction of SEACEN banks was sizeable yet not substantial and did not last very long.

The final jump in the index from 56% to 60% took place in the first week of November as the Indian government decided to pull all 500 and 1000 Rupee banknotes from the circulation. The decision which perhaps will help the Indian banking system grow faster in the long-run, hurt Indian bank stocks in the short-run by squeezing the liquidity available in the economy. As we have already discussed the Indian liquidity squeeze episode earlier, we can now move to the dynamic analysis of connectedness after including GSIBs, as well as the major Japanese and Australian banks. In Figure 7, we plot the 150-day total dynamic connectedness index for SEACEN banks before and after adding GSIBs as well as major Australian and Japanese banks (See Table 4 for a list of these banks). The connectedness index, on average, jumps by 10 percentage points after the inclusion of the GSIBs as well as the major banks of Australia and Japan. Such a difference is expected, as GSIBs generate substantial volatility connectedness among each other as well as towards banking systems around the world.

Figure 7
Dynamic Total Volatility Connectedness – SEACEN Banks with GSIBs and Banks from Australia and Japan (January 5, 2004 - December 31, 2016)



Over time the difference between the two connectedness indices fluctuates between 8 and 12 percentage points. The difference between the two is low (between 4 and 8 pp) to begin with. As we have already contemplated before, at the beginning of the sample period the connectedness among the SEACEN banks was high and it declined in a matter of months. The difference goes up 16 percentage points during the Greek sovereign debt crisis of 2010. While the European bank stocks were significantly affected from the Greek sovereign debt crisis, the impact of the crisis on American banks were quite limited and hence it generated little volatility connectedness towards the SEACEN banks. A limited increase in the difference between the two total connectedness measures is observed during the summer of 2011, when the European debt troubles was coupled by S&P's decision to downgrade the US government long-term debt from AAA to AA. However, this time SEACEN bank stocks were also affected. That is why the difference in total connectedness measures went up to only 12 percentage points and declined quickly.

Since 2014, there is an upward move in the difference between the two connectedness measures. This is clearly an indication that the increase in volatility connectedness since 2014 has in greater part been from GSIBs to SEACEN banks without an equal increase in the "to connectedness" of the region's banks. There are several factors behind the increase in GSIBs to connectedness. First of all, starting in 2012, many American and European GSIBs had been subject to huge fines and penalties issued by the regulators. This increased the volatility of bank stocks in the US and Europe. Second, in October 2014, there was a flash crash in the US sovereign bond markets when the yield on the US 10-year note fell 34 basis points from 2.2% to as low as 1.86% in a matter of several minutes. After the flash crash, US and European bank stock volatility increased for a while. Then in the summer of 2015, the global financial markets started to bounce back and forth, as bad news from the Chinese private loan markets increased the expectations about a possible meltdown in Chinese financial markets. The troubles of the Chinese markets, were to some extent, captured by the presence of Chinese banks in our analysis. However, the fear factor about a possible Chinese crisis led to a substantial increase in volatility among GSIBs. Then in early 2016, there was the CoCo (short for "contingent convertible") bonds trouble first observed in the case of Deutsche Bank and was also viewed as a problem for other banks. And finally, the unexpected Brexit decision on June 23 affected GSIBs more than others, and GSIBs spread the increased volatility to the SEACEN region.

6.2 Dynamic Total Directional Connectedness

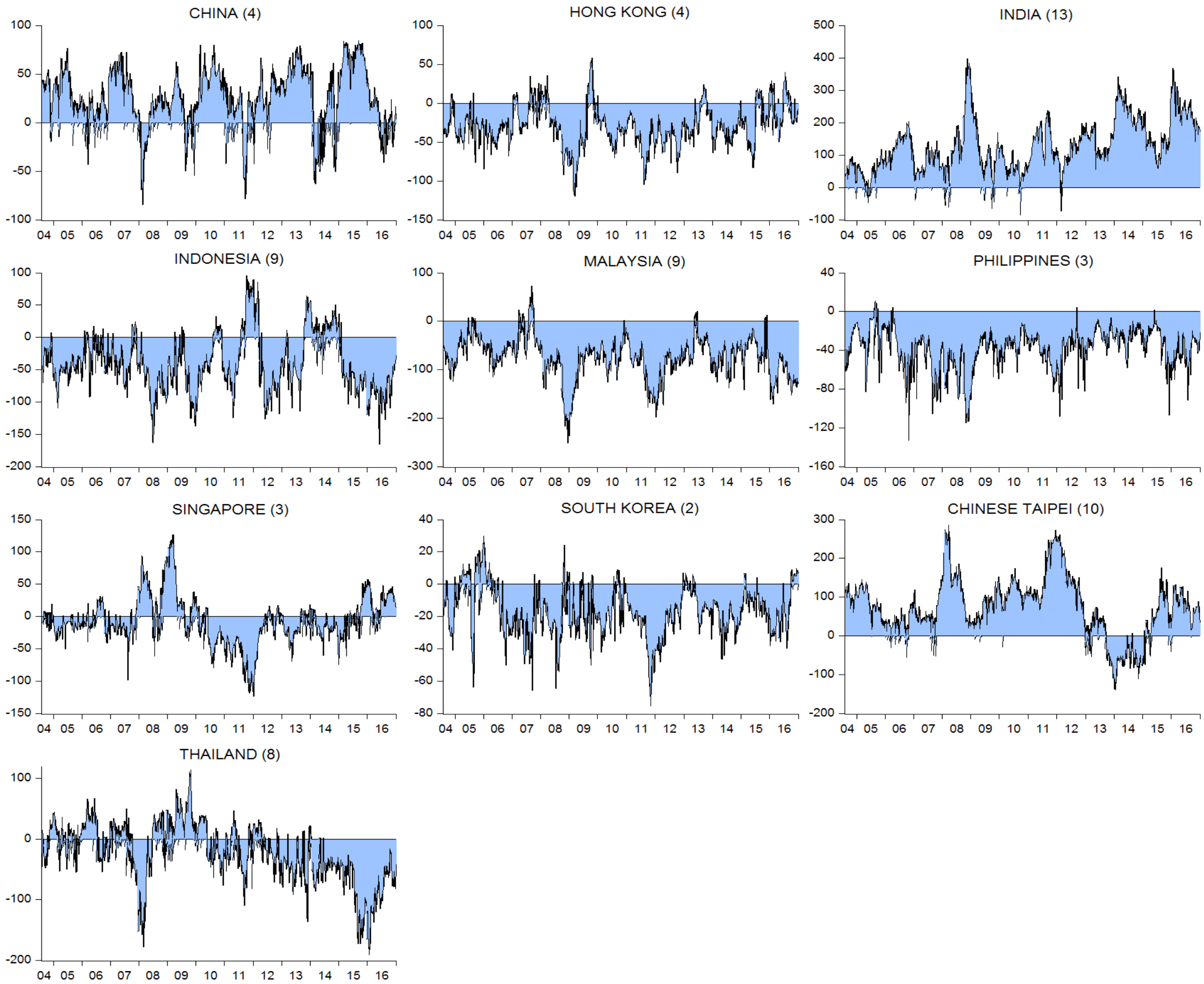
In the previous subsection, we focused on the behavior of the total volatility connectedness index for the SEACEN region bank stocks. While the total index gives us a clue about the state of affairs in the region's banking, it does not provide detailed information about how the volatility shocks travelled within the region. In this section, we have a closer look at the total directional connectedness of each economy's banking system. In particular, our analysis will aim at identifying the major banking systems (and sometimes banks) that generate volatility connectedness to others in the region.

First, we present the dynamic net directional volatility connectedness across banking systems in Figure 8.[7] Instead of presenting both "to others" and "from others" connectedness measures for each economy, we present net connectedness as the difference of "to" and "from" connectedness measures. As we have already discussed above, we included only banking sectors of 10 economies in our sample. It is striking to see that the banking systems of India, Chinese Taipei and China tend to generate positive net volatility connectedness to others throughout the whole period. While it is true that banks in these three economies tend to be larger than their counterparts in other economies in the region, it is interesting to observe that they are the main drivers of bank volatility connectedness across the region.

Perhaps one may conclude that Indian (13) and Chinese Taipei (10) banks generate "net" connectedness to others, because they outnumber banks in other economies. Other economies such as Malaysia (9), Thailand (8) and Indonesia (7) also have a high number banks in our sample, but with some exceptions they tend to have negative net connectedness. It is not only the number of banks representing the economy but also the average size of these banks that determines whether they have positive or negative net connectedness.

7. We present the dynamic net connectedness of individual banks in Figures A1 through A6 in the Appendix.

Figure 8
Dynamic Net Volatility Connectedness at Economy-level



For an overwhelming number of subsamples considered, Indian banks generate positive net connectedness to the banks in other economies. In the aftermath of the Lehman Brothers' collapse the net volatility connectedness from all Indian banks to other banks in the region reached a high of 380% net volatility connectedness. Actually, during the global financial crisis several Indian banks went into trouble due to their financial investments in the American asset markets. For example, ICICI, the second largest bank of India, came very close to collapse after the Lehman debacle. It was already known in India that ICICI invested the most in the US financial markets among Indian banks. In particular, its investment on collateral debt obligations (CDOs) and CDSs made headlines immediately after Lehman's collapse. As a result, ICICI bank's (ICBK in our sample) market value declined by 45.5% from September 15 to October 10, 2008, whereas other private Indian banks lost only 19.4% of their market value. Eventually, ICICI survived the crisis with the help and assurances from Reserve Bank of India. However, in the meantime, it generated substantial volatility connectedness among Indian banks and banks in the SEACEN region.

At the end of 2013 - early 2014 and following the Chinese troubles in August 2015, the net connectedness from Indian banks to all others reached levels higher than 300%. The increase in connectedness in late 2013 could be an outcome of the so-called "taper tantrum" that started affecting other emerging markets after Bernanke's speech on June 20, 2013.

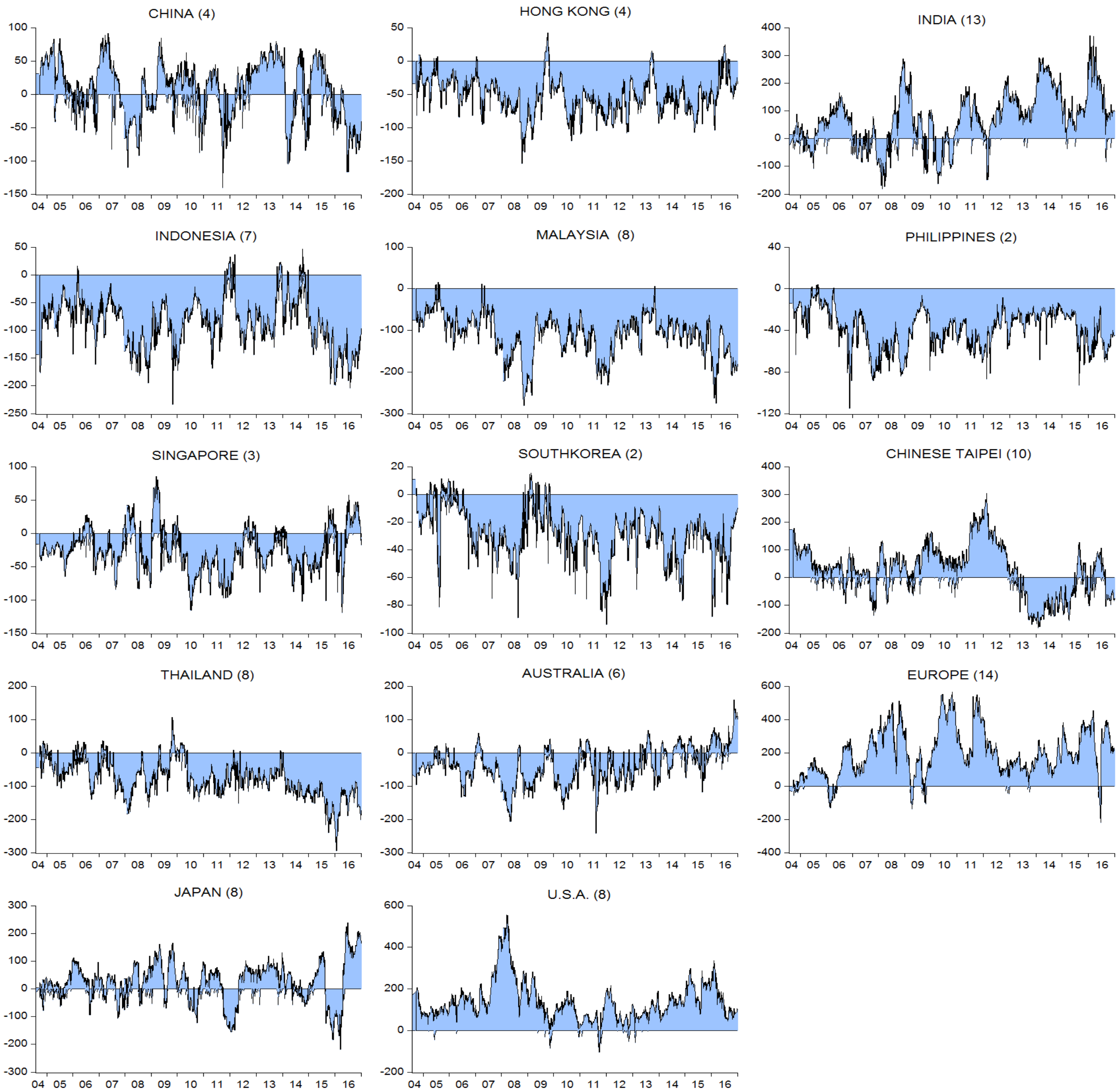
While Indian banks' net volatility connectedness to others increased following the collapse of Lehman Brothers in the last quarter of 2008, Chinese Taipei banks' net volatility connectedness jumped to 280% at the end of 2007 and early 2008. Even though, the net connectedness of Chinese Taipei banks declined slightly in 2008, it stayed well above 150% until the beginning of the Lehman saga. As the net connectedness of Indian banks increased, that of Chinese Taipei banks declined in late 2008 and stayed in the 20-40% range before climbing up gradually in the second half of 2009 and throughout 2010. Chinese Taipei banks' connectedness jumped up significantly following the increased worries about the Euro debt crisis in the summer of 2011 and the US government's credit downgrading in August 2011.

There are only four Chinese banks included in our analysis. We would have liked to include a larger number of banks from China, but the majority of the Chinese banks are state-owned. As a result, we could not incorporate a larger part of Chinese banking system in the analysis. Despite that fact, being the largest banks included in the analysis, shocks to Chinese bank stock return volatilities are expected to have significant influence over other bank stocks. In Figure 8, after Indian and Chinese Taipei banks, Chinese bank stocks come out very strong in terms of net connectedness to others. For an overwhelming portion of the 13 years covered in our analysis, the net connectedness of the Chinese banks stay positive and mostly fluctuate around 50%. There are also short periods (such as January 2008, when the Federal Reserve had to reduce its policy rate twice in a month) during which the net connectedness drop significantly to negative territory, and as low as -80%. All these episodes lasted only a short while, except for the first half of 2014 and the second half of 2016.

In terms of generating connectedness to others, Thai banks follow Indian, Chinese Taipei and Chinese banks. Thai banks generate connectedness earlier in the sample, from 2004 to 2007. Their net connectedness increased after the collapse of Lehman Brothers and stayed high until mid-2010. Since then, the net connectedness of the Thai banks tended to be on the negative side, with occasional small positive net contributions to the bank volatility connectedness in the region.

After analyzing the economy-level net connectedness patterns in the SEACEN region, we now focus on the analysis with an expanded sample of banks including GSIBs as well as the major Australian and Japanese banks. Demirer et al. (2017) showed that large GSIBs of the US and Europe tend to generate substantial connectedness to other top global banks around the world. With that result in mind, we expect that the net connectedness of SEACEN banks as well as the SEACEN banking systems to decrease with the inclusion of GSIBs. Yet, we do not expect the relative positions of banks and/or economies in terms of net connectedness to change dramatically. In Figure 9, we present the net connectedness measures at the economy-level and compare them with the corresponding measures when only SEACEN banks are included in the analysis (see Figure 8).

Figure 9
Dynamic Net Connectedness at Economy-level
(with GSIBs, Australian & Japanese Banks)



Before going into an economy-level comparison, it is important to focus on the dynamic net connectedness of American and European GSIBs, and major Japanese and Australian banks. Consistent with the Demirer et al. (2017) results, European and US GSIBs generate substantial connectedness to others throughout the 2014-2016 period. American GSIBs' net connectedness increased significantly following the liquidity crisis of August 2007 and reached a peak level (above 500 percentage points) in January 2008. Declining afterwards, their net connectedness was still above 200 percentage points in late 2008, after Lehman's collapse, and early 2009. US GSIBs' net connectedness declined significantly afterwards, falling below 100 percentage points until 2014. Even after 2014, its level increased above 200 percentage points only after the US bond market flash crash in October 2014 and ensuing the increased worries about a possible financial crisis in China in the summer of 2015. The European GSIBs tend to have much higher net connectedness after 2008, and obviously during the first and second phases of the European sovereign debt and banking crisis in 2010 and 2011. Even though they had lower net connectedness in 2013, the net connectedness of European GSIBs has increased significantly since 2014, fluctuating between 300 and 400 percentage points.

As expected, the inclusion of GSIBs and the major Australian and Japanese banks in the analysis affects the absolute levels of net connectedness measures of the SEACEN region economies. Net connectedness of Chinese, Indian and Chinese Taipei banks as well as other economies decreases significantly with the inclusion of GSIBs. While Indian banks as a whole, had positive net connectedness throughout the whole sample when only SEACEN banks are included in the analysis (see Figure 9), with the inclusion of GSIBs, their net connectedness move into negative territory for 2007, most of 2008 (pre-Lehman collapse) and in all of 2010. Indian banks' net connectedness from 2011 onwards stay positive, yet lower compared to Figure 8 when only SEACEN banks are included.

Net connectedness of Chinese banks declined even more than that of Indian banks with the inclusion of GSIBs, major Japanese and Australian banks in the analysis. Their net connectedness turned negative for the US and European financial crisis episodes as well as since late 2015. Indeed, Chinese banks started generating high connectedness in late 2014, through August 2015. However, as the GSIBs are affected very much by the Chinese financial market worries, they started spreading volatility shocks globally, as is evident in the significant increase in the net connectedness of US and European GSIBs.

When considered in isolation, economy-level bank net connectedness of Hong Kong, Indonesia, Malaysia, the Philippines and South Korea were mostly in the negative territory (see Figure 8). With the inclusion of GSIBs, major Australian and Japanese banks, the net connectedness of these economies moved further into the negative territory. In addition, net connectedness of Thai banks, that used to be mostly in the positive territory for most of the period from 2004 to 2010 moved into negative territory for the whole sample period from 2004 to the end of 2016. Among the SEACEN economies, Singapore is the only one whose economy-level net connectedness stayed more or less unchanged with the addition of GSIBs and major Australian and Japanese banks.

In general, net connectedness of Japanese banks have been on the positive side, with occasional negative values. However, unlike US and EU banks, Japanese banks, which also include GSIBs, never generated substantial connectedness to other, have generated positive net connectedness, with occasional negative net connectedness. Recently, Japanese banks' net connectedness fluctuates wildly. Following the 8.5% drop in the Shanghai stock index on August 24, 2015, the Nikkei 225 index fell by 4.6% on the same day. Immediately, the net connectedness of Japanese banks dropped from higher than 100% all the day way to negative territory, eventually moving below -100 percentage points. After fluctuating below -100 percentage points, Japanese banks' net connectedness then make a quick turnaround in May 2016. Contrary to market expectations, the Bank of Japan's monetary policy committee decided not to change its monetary policy stance in its regularly scheduled meeting on April 28, 2016. As a result of this decision, the net connectedness of the Japanese banks that was previously fluctuating around -50 percentage points, moved up to 200 percentage points by the end of May 2016. Since then, Japanese banks' net connectedness fluctuates between 100-200 percentage points.

6.3 Pairwise Directional Connectedness and the Network Graphs

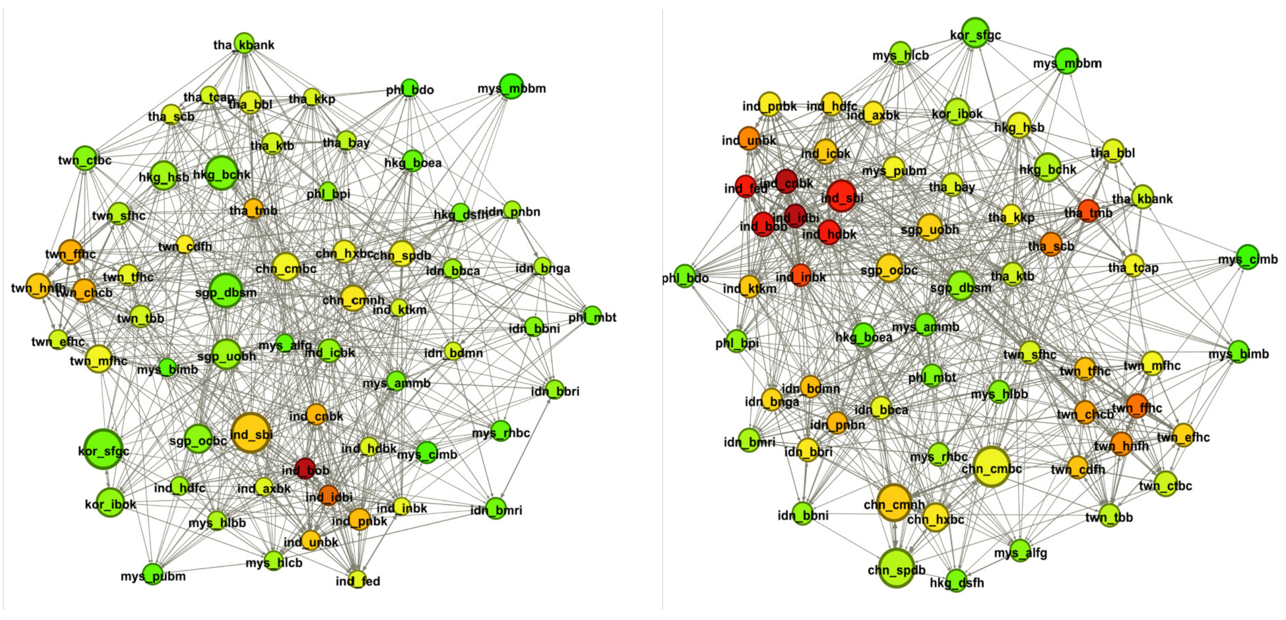
The dynamics of total connectedness provides one with a clear understanding of the financial market developments influencing the volatility connectedness across major SEACEN region bank stocks. The analysis of economy-level net connectedness measures in the SEACEN region first in isolation and then with the inclusion of GSIBs and major Australian and Japanese banks in the sample provides us with important clues as to how the banks of the region are connected with each other.

With this background information, it is now possible to have a close inspection of the volatility connectedness network on certain critical days. We start the analysis of the connectedness network graph with the May 10, 2006 decision of the Federal Reserve's Federal Open Market Committee (FOMC) to increase the federal funds rate target from 4.75 % to 5% with an indication of a further increase to 5.25% in its June 2006 meeting. The FOMC's decision initiated a period characterized by the unwinding of carry trades originating from the US and Europe to take advantage of high returns in the emerging market (EM) economies. As the cost of borrowing in the US was increasing further, many investors found it difficult to roll over their increasing-cost US debts to finance their investment in EM assets. This started a reversal of capital flows to the EMs. As a result, many EM bank stocks are affected from this decision.

As a result of this decision, the total connectedness index increased from 45.7% on May 2, 2006 to 52.2% on June 22, 2006. Figure 10 depicts the connectedness network graphs of the SEACEN banks on May 2, 2006 (before FOMC's May 2006 meeting) and on June 22, 2006, (after FOMC's June 2006 meeting). In Figure 10(a), there was low directional connectedness among the SEACEN banks. The Bank of Baroda (ind.bob) followed by IDBI bank (ind.idbi), both Indian banks, were generating the two highest levels of connectedness to others in May 2006. Even though there were some other Indian and Chinese Taipei banks with orange-colored nodes, indicating a medium level of connectedness to others, the majority of the banks in the network were generating low levels of connectedness. When we move to the network graph for June 22, 2006, the number of green-colored nodes decreases while the number of yellow-, orange-, red- and crimson red-colored nodes increases significantly. The majority of Indian banks now have nodes with crimson red and red colors. In terms of increased connectedness, Chinese Taipei banks follow the Indian banks. Banks of other economies also started to generate higher connectedness to others.

Next, we focus on the liquidity crisis of August 2007, which was triggered by BNP Paribas August 9, 2007 decision to freeze US$2.2 billion worth of three hedge funds it owned, due to the huge losses they made from their investments in the US subprime mortgage market. This announcement brought about a rush to liquidity by all major US and European banks and huge sell-offs of bank stocks on two sides of the Atlantic.

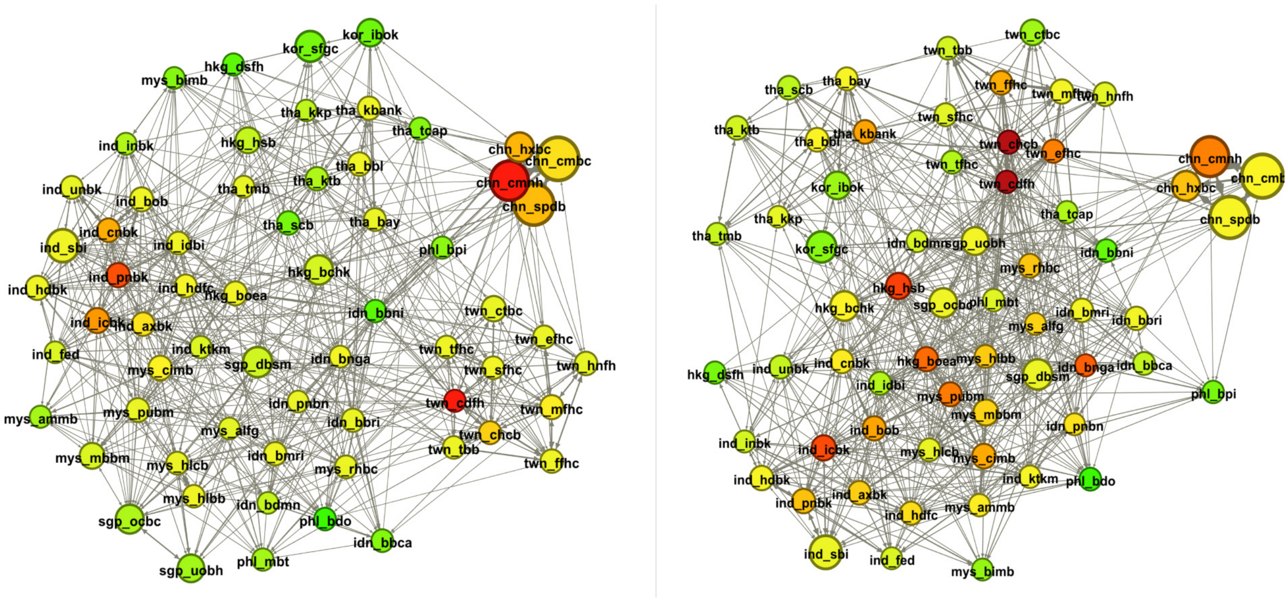
Figure 10
After the Fed Rate Hike in May-June 2006



(a) May 2, 2006 (index=45.7%) (b) June 22,2006 (index=52.2%)

In order to see the effect of the liquidity crisis on SEACEN bank volatility network connectedness, we plot the volatility connectedness on July 25 (before the liquidity crisis) and on August 17 (after the crisis). While the total connectedness was 50.5% before the crisis, it jumped to 58.4% once the liquidity crisis hit the markets. The increase in total connectedness is also visible in the increased thickness of the pairwise connectedness measures once the liquidity crisis hit. Chinese, Chinese Taipei and Thai (along with Korean) banks stay separately after the crisis hit, but the connectedness of banks from other economies in the region increased significantly as can be seen in the thickness of edges among them. Three Chinese Taipei, two Hong Kong, one Indian, one Indonesian and one Malaysian bank turned out to have higher connectedness to other banks in the region. Interestingly, while Chinese banks were generating higher connectedness to others in the pre-crisis period, once the crisis hit, their connectedness to others slightly declined as indicated by the change of node colors from red to orange, and orange to yellow etc. When we compared the bank network connectedness in July-August 2007 with those in May-June 2006, the increased connectedness among the SEACEN region banks are quite visible, both in terms of the colors of bank nodes as well as the thickness of the edges among bank nodes.

Figure 11
Liquidity Crisis – August 2007

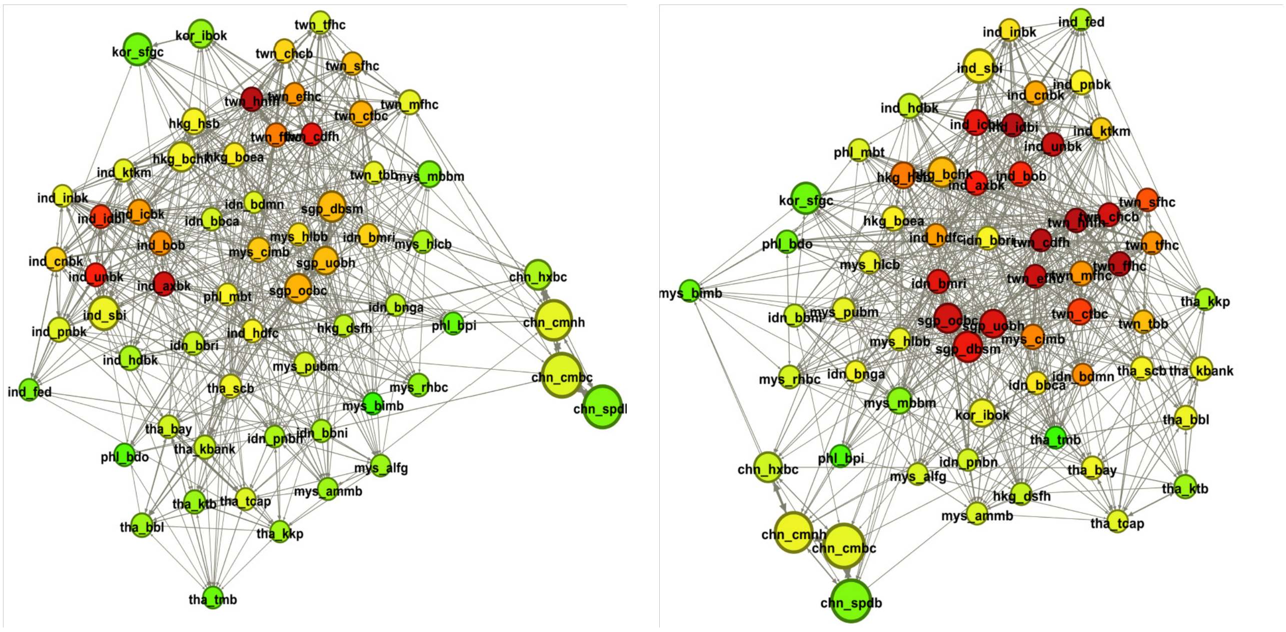


(a) July 25, 2007 (index=50.5%)   (b) Aug 17, 2007 (index=58.4%)

The last quarter of 2007 was quite difficult for many banks in the US and Europe. Following the liquidity crisis, banks started to announce huge losses. After years of constantly increasing profits, the huge losses of the third and especially the fourth quarter of 2007 had shaken the trust on the US and European banking systems. As the 2007 fourth quarter balance sheets were announced in January with billions of dollars of losses, bank stocks came under great pressure. Observing the immense trouble the US banks were already in, in an unscheduled emergency meeting on January 21, one week before its scheduled meeting, the Federal Reserve's FOMC decided to lower the federal funds target rate by 3.5%. This was the biggest cut in policy rates in US policy rates in nearly 24 years. Despite that fact, the bank stock return volatilities increased not only in the US but everywhere else as well.

The comparison of the two graphs in Figure 12 clearly show how bad the bank stock return volatilities in the region were affected even though they were located thousands of miles away. The total connectedness index jumped from 55.8% on January 14 to 63.4% on January 25. The jump in the index clearly reveals how the SEACEN region's bank stock volatilities increased in a matter of 10 days. While on January 14, there were only four to five banks with red-colored nodes, on January 25 this number jumped to 15. After the FOMC's meeting, on January 25 almost all Chinese Taipei banks were generating high levels of connectedness to others, revealed by their node colors turning into crimson red, red and orange. In terms of the "to connectedness," Chinese Taipei banks were followed by Indian, Singaporean, Hong Kong and a couple of Indonesia banks. Others, including Chinese, Thai, Malaysia, South Korean and Philippine banks, were all on the receiving end. This clearly shows that these banks did not have direct or indirect involvement in the toxic mortgage backed securities which originated in the US subprime mortgage markets.

Figure 12
Two FOMC Meeting in a Month – January 2008

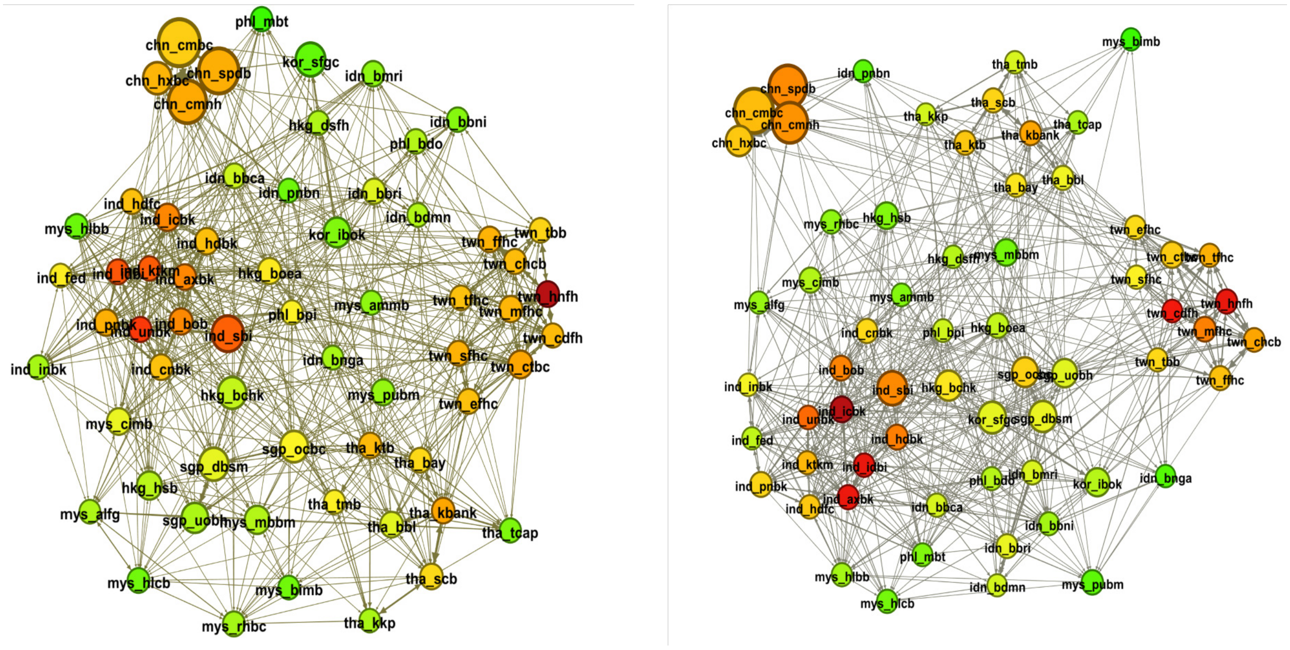


(a) Jan. 14, 2008 (index=55.8%) (b) Jan. 25, 2008 (index=63.4%)

The bankruptcy of Lehman Brothers on September 15, 2008, is now accepted as the most important development in financial markets that transformed the US financial crisis into a global one. The volatility in US stock markets increased tremendously after Lehman's bankruptcy, especially when it became apparent that the giant insurance company AIG could easily go bankrupt. As Lehman collapsed, AIG, which insured Lehman's corporate debt through credit default swaps, had to make tens of billions of dollars of payments to CDS holders on Lehman corporate debt. Even though the US Treasury and the Federal Reserve together poured US$182 billion to bail-out AIG, the markets could not be calmed down. The crisis is became a global one, especially in the last quarter of 2008. The total connectedness index for the SEACEN banks reached its peak on January 12, 2009.

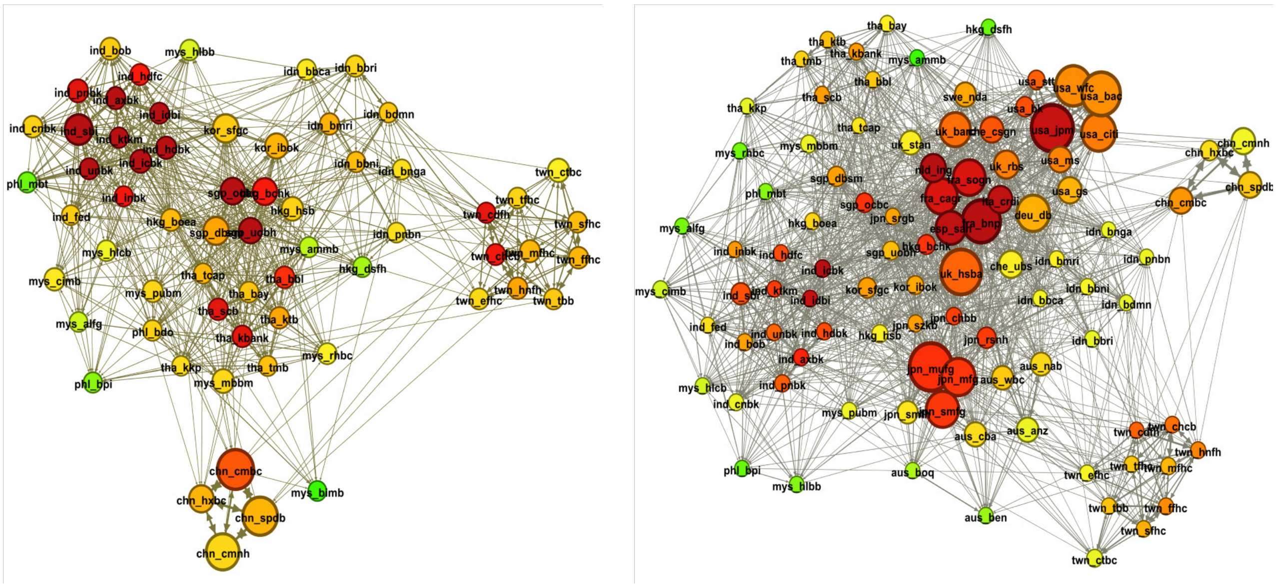
In order to analyze the SEACEN region's bank network connectedness before and after the Lehman Brothers' collapse, we plot the network connectedness graphs on August 29, 2008 and October 1, 2008. The total connectedness index increased from 51.9% on August 29 to 58.6% on October 1st. As a result, the node colors of some banks turned into orange, red or crimson red, but not as much as one would expect in a crisis situation. For example, a comparison of the network graphs on October 1, 2008, with that of January 25, 2008, reveals that there were more banks generating significant connectedness on January 25 than October 1, 2008. This indicates that even though US financial institutions were suffering substantial degrees of volatility connectedness immediately after the collapse of Lehman Brothers (see Demirer et al. (2017)), the impact on SEACEN banks as of October 1, 2008 did not reach high levels.

Figure 13
Before and After Lehman's Collapse – Aug. - Oct. 2008



(a) Aug. 29, 2008 (index=51.9%)   (b) Oct. 1, 2008 (index=58.6%)

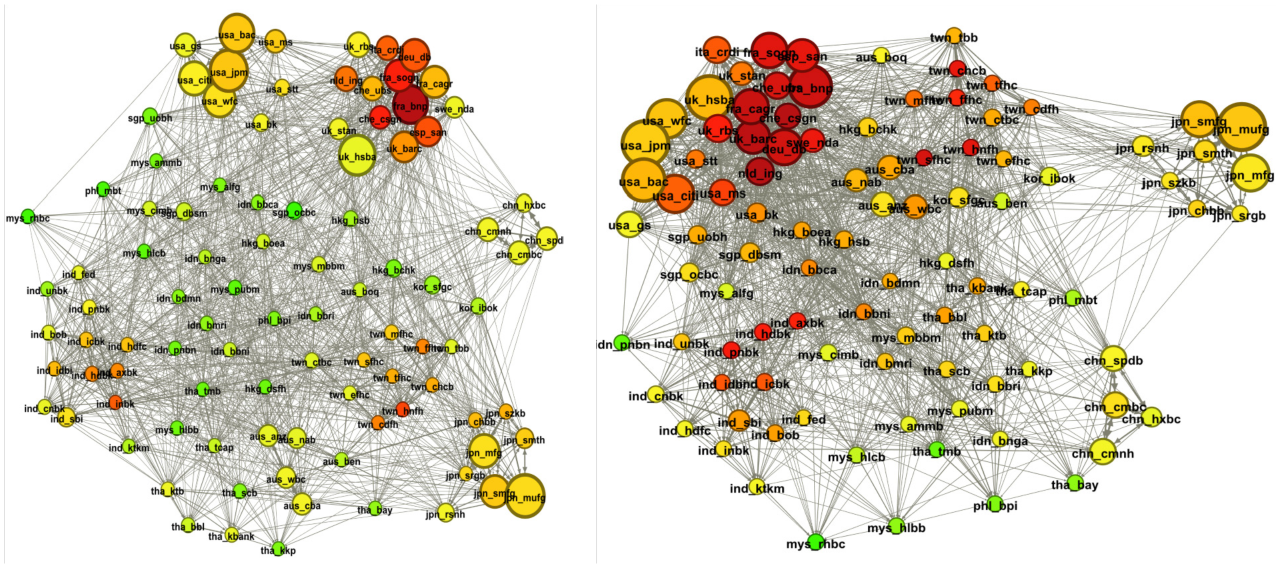
Figure 14
Global Financial Crisis - Jan. 12, 2009 (with and without GSIBs)



(a) SEACEN banks only (index=69.2%)   (b) with GSIBs, AUS, JPN banks (index=76.6%)

As the US financial crisis deepened further with the troubles of AIG and other financial institutions, US and European financial institutions started generating a high degree of connectedness to the rest of the world, including the SEACEN region. As a result, the total connectedness index for SEACEN region banks reached its maximum on January 12, 2009 (see Figure 5). In order to grasp the high degree of connectedness from the US and European GSIBs to the SEACEN region, in Figure 14 we plot the volatility connectedness of SEACEN banks on January 12, 2009, with and without GSIBs. The fact that the color of a significant number of bank nodes turned into orange, red or crimson red indicates how much the region's banks were generating volatility connectedness to each other four months after the collapse of Lehman Brothers. Among the SEACEN banks, Indian banks were the most severely hit, followed by Singapore, Hong Kong and Thai banks. Chinese Taipei banks as well as the Chinese banks generated lower connectedness compared to the banks from India, Singapore, Hong Kong and Thailand. The troubles of ICICI Bank of India over this period, which have already been discussed earlier, reduced investors' confidence for Indian banks and that is why the majority of them came under substantial pressure in the financial markets.

Figure 15
Euro Crisis & U.S. Gov. Debt Downgrade – with GSIBs, AUS and JPN Banks

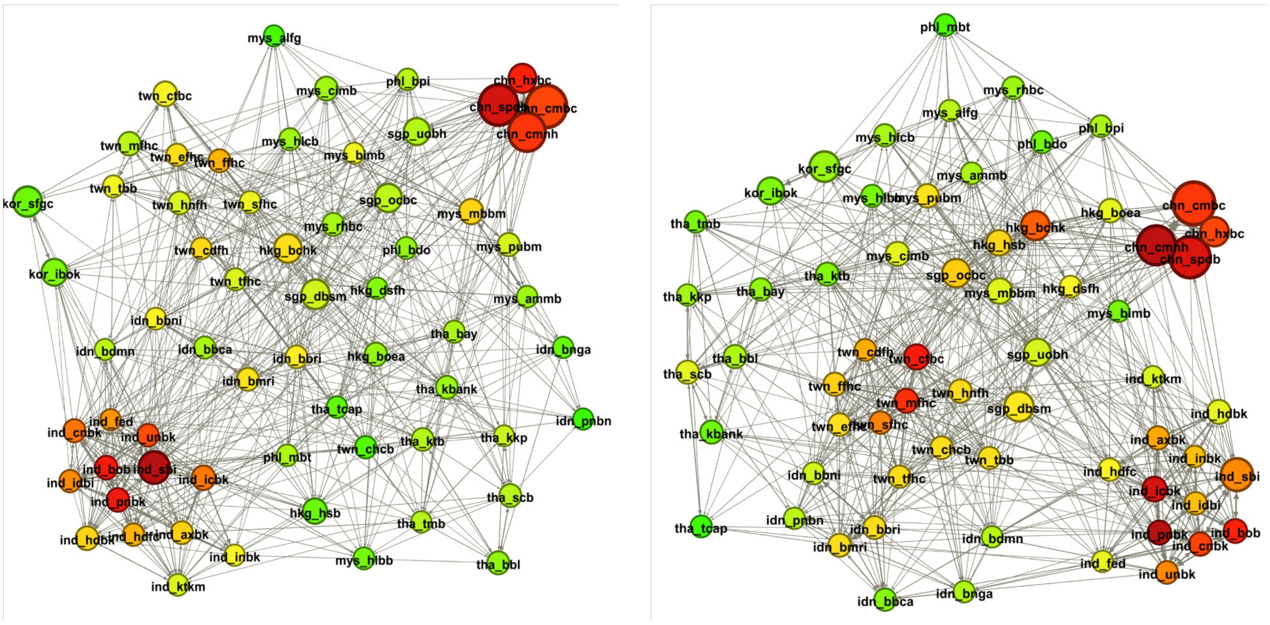


(a) August 4, 2011 (index=66.6%) (b) October 4, 2011 (index=77.7%)

Next, we focus on the developments in global financial markets during the second phase of the European sovereign debt and banking crisis coupled with the grading of the US long-term government debt (see Figure 15). Before the Standard and Poor's decision to lower the US government's long-term credit rating from AAA to AA on August 4, 2011, European GSIBs were generating high volatility connectedness on a global scale, while American, Japanese and Australian banks had orange to yellow nodes, indicating that they were generating mid-level connectedness to others. In the SEACEN region, on the other hand, Chinese Taipei and Indian banks were generating high connectedness to others in the region. Chinese banks, as well as others in the region generate relatively low connectedness on August 4, 2011 (see Figure 15(a)).

After S&P's decision to lower the US government's credit rating, the pairwise volatility connectedness does not change very drastically immediately. However, when we roll the subsample to October 4, 2011, the total index with GSIBs increases from 66.6% on August 4 to 77.7% on October 4, 2011 (see Figure 7). The bank network connectedness graph also changes significantly, with more orange- and red-colored nodes dominating the scene along with thicker edges (See Figure 15(b)). As of October 4, all European GSIBs (except for HSBC) generated very high levels of connectedness to others, while volatility connectedness from US GSIBs to others was lower. The red- and orange-colored bank nodes make it clear that Chinese Taipei and Indian banks were actually generating more connectedness than the US GSIBs. Japanese and Chinese banks continue to generate only medium-levels of connectedness to others and stay further away from the European and US GSIBs. Australian banks were affected significantly by the European crisis as indicated by their orange-colored bank nodes that move closer to the European GSIBs cluster. Major banks of Singapore and Hong Kong also move closer to the US GSIB cluster, with their node colors turning to all green to orange. Indonesian, Thai and some Malaysian banks also generated medium-levels of connectedness as indicated by their orange and yellow-orange colors.

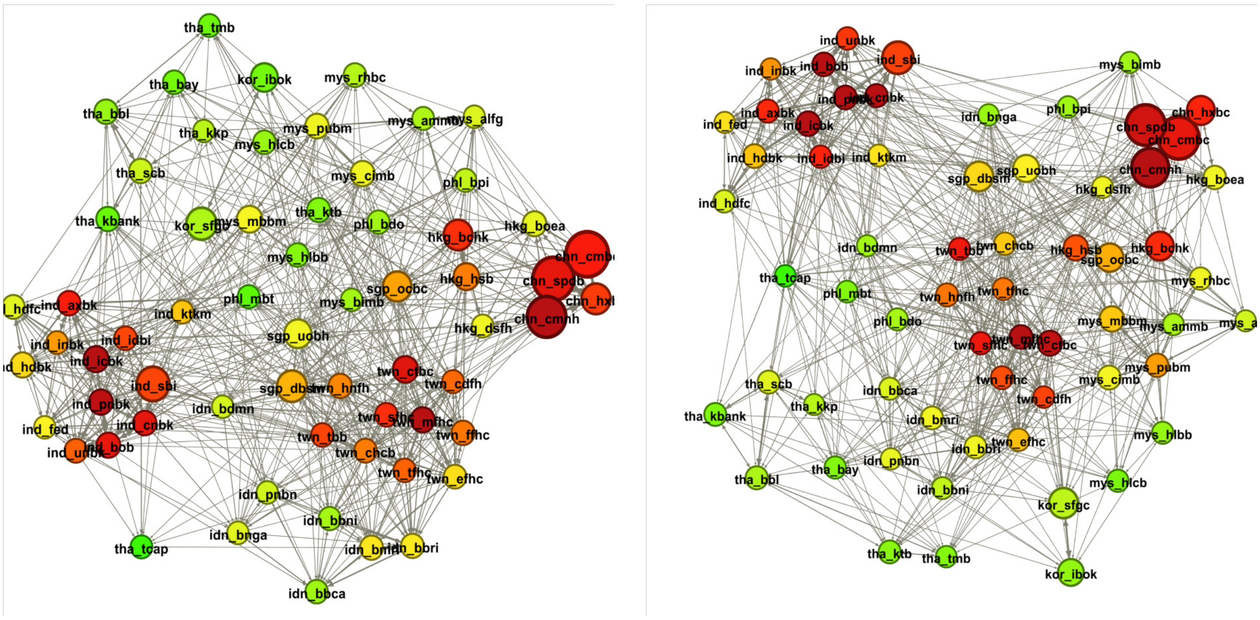
Figure 16
Increased Worries about Chinese Financial Crisis – I



(a) Mar 12, 2015 (index=49.4%)　　(b) Aug 20, 2015 (index=50.8%)

2014 was mostly an uneventful year. Yes, there were some skirmishes affecting various asset markets around the world, such as the US bond market flash crash on October 14, 2014 but its effects on financial institution stocks were rather limited. Then came 2015. The main development in global financial markets was the increased worries about the Chinese financial sector, shadow real estate loans by banks and non-bank entities, in particular. The stock return volatilities of the Chinese banks started to go up in the first quarter of 2015. Even though, the total connectedness index for the SEACEN banks was only 49.4%, on March 12, 2015 the net connectedness of Chinese banks increased to 74%, second only after Indian banks (see Figure 8).

Figure 17
Increased Worries about Chinese Financial Crisis – II

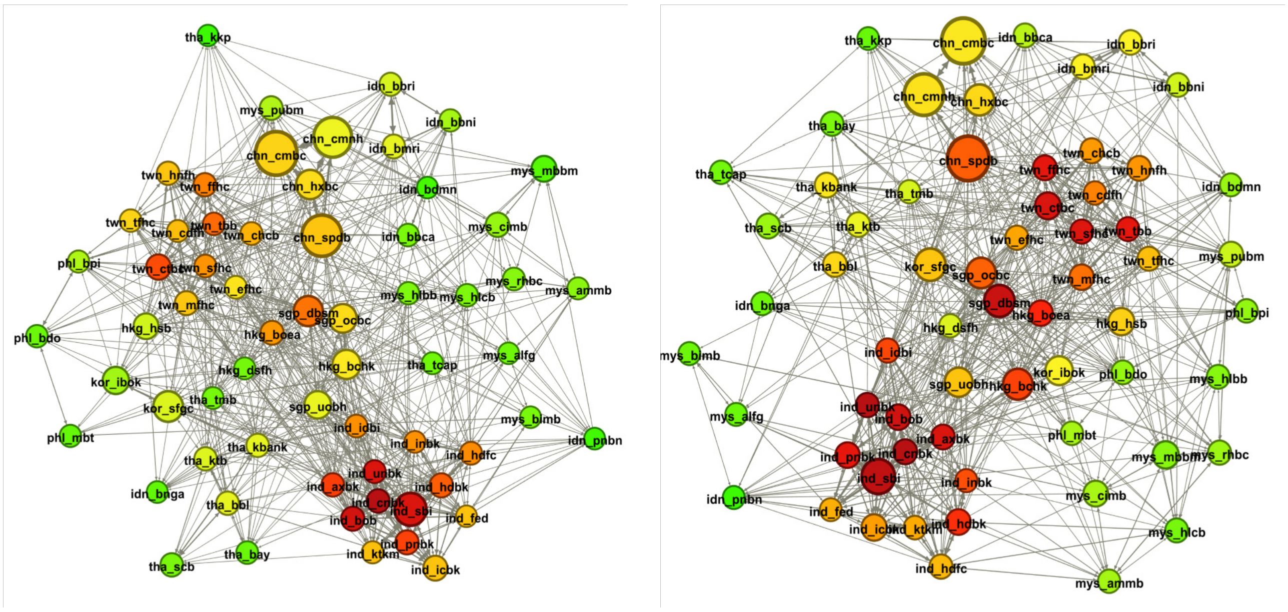


(a) Aug. 26, 2015 (index=60.1%) (b) Sep. 11, 2015 (index=61.3%)

When we have a look at the SEACEN bank network connectedness on March 12, 2015 (Figure 16(a)), we face an even starker picture. All four Chinese banks generate high connectedness to others as indicated by their respective nodes colored in crimson red and red. Aside from the Chinese and Indian banks, however, the rest of the SEACEN banks generated low connectedness to other banks in the region. The worries about the possibility of a financial crisis in China started to intensify in the summer of 2015 and gradually spread to the global financial system. Meanwhile, the SEACEN region total bank connectedness index increased to 50.8 by August 20. As the total index was increasing, Chinese Taipei banks also joined the Chinese and Indian banks to generate higher connectedness to others.

On August 23, world stock markets and oil prices plunged as a global selloff accelerated on fears about the health of Chinese economy. As a result of the global selloff, the connectedness index jumped by 10 percentage points to reach 60.1% by August 26. At the same time, node colors of almost all Chinese Taipei and Indian banks along with banks from Hong Kong and China turned into orange, red, or crimson-red (Figure 17(a)) reflecting a high level of volatility connectedness they generated to others in the SEACEN network. Chinese Taipei banks moved closer to banks in mainland China and Hong Kong, as their pairwise connectedness with Chinese and Hong Kong banks increased. This trend continued and the total connectedness increased to 61.3% by September 11, 2015 (see Figure 17(b)).

Figure 18
U.K. Brexit Decision – June 2016



(a) June 23, 2016 (index=56%) (b) June 24, 2016 (index=60.2%

The last two episodes that led to a jump in the volatility connectedness across SEACEN banks are the so-called Brexit, the British decision to leave the European Union as a member country (on June 24, 2016) and the Indian government's decision to withdraw 500 and 1000 rupee bills from circulation (on November 9, 2016). While both led to significant increases in the total connectedness index, their impact on directional connectedness also reveal substantial change.

On June 23, 2016, the day of the British referendum, public opinion polls indicated a slight tendency in favor of remaining in the EU. That is why the stock markets were not in a reactionary mood. Calm in the UK and the rest of the world was quite evident. The connectedness index was relatively low, and only a few Indian, Chinese Taipei and Singaporean banks were generating higher connectedness to other banks in the region. With light orange and yellow node colors, Chinese banks were generating only a medium level of connectedness (see Figure 18(a)).

When the final result of the British referendum was announced, that the majority of British voters who went to the polls supported the Brexit decision, it was a rather unexpected outcome for the whole world. On June 24, 2016, the global markets reacted substantially. British banks' share prices plunged in one day. For example, share prices of Lloyds and Barclays went down 21% and 18%, respectively. With huge one-day drops in share prices, the volatility of British and European and to some extent American bank stocks jumped up. British and European banks generated substantial volatility connectedness to others.

Without even including GSIBs in the analysis, we can easily see the impact of the Brexit in the SEACEN region. The total connectedness index increased from 56% to 60.2% within one day. Nodes of the majority of Indian, Chinese Taipei, Hong Kong and Singaporean banks turned into orange, red and crimson red colors, reflecting the significant increase in their directional connectedness to others. However, as we rolled the sub-sample window, the impact of the Brexit decision started to decline quickly and dissipated over time.

The Indian government's decision to withdraw 500 and 1000 rupee bills from circulation increased the short-run uncertainty for the Indian banks. However, its impact on the rest of the region was very limited. As we have discussed above, even the increase in the net connectedness of Indian banks was quite limited after the Indian government's decision to withdraw large sums of cash from circulation (See Figure 9).

7. Conclusions

We applied the DYCI methodology to daily bank stock return volatilities to analyze the bank volatility connectedness in the SEACEN region in the period from 2004 to 2016. Our results provide important insights to the behavior of the SEACEN region's major bank stocks over time. SEACEN banks have been significantly affected by the global financial crisis as well as the European debt and banking crisis, as reflected in substantial increases recorded by the total and directional connectedness measures during the major turning points from the US financial crisis into a global financial crisis.

In the static analysis, we identify economy-level clusters in the banking volatility network: Major Indian, Chinese Taipei and Chinese banks generate volatility connectedness to banks in other economies of the region. In our flexible empirical framework, we expand the analysis of volatility connectedness to include GSIBs, as well as major Australian and Japanese banks in the sample. Once included in the analysis, American and European GSIBs generate substantial volatility connectedness to SEACEN region banks. Even though their importance declined significantly with the inclusion of GSIBs, the Indian, Chinese Taipei and Chinese banks continue to play an important role in spreading banking sector shocks to other economies in the region.

In the dynamic analysis, we show that the volatility connectedness increased substantially during the US financial crisis (from 2007 to 2009) and during the European sovereign debt and banking crisis in 2011. Even though, the total connectedness declined in 2012, it increased again in the second half of 2013 due to what is now called Federal Reserve's "taper tantrum" decision; in August 2015 when the worries about a Chinese financial crisis climaxed; in June 2016 following the Brexit decision and finally in November 2016 following the Indian government's decision to withdraw 80% of liquidity from the financial markets. The dynamic analysis reveals that the increased volatility connectedness since 2013 turns into an upward trend due to the presence of GSIBs. Without GSIBs, the within-region volatility connectedness does not follow a strong upward trend.

Similar to the static analysis, the dynamic analysis results show the critical role played by GSIBs in terms of generating connectedness to the region's banks. In the dynamic analysis, Indian and Chinese Taipei banks tend to generate volatility connectedness to others over the majority of systemic events. Finally, the analysis of the region's bank network connectedness reveals that during systemic events, the region's bank volatility network becomes tighter; banks from different economies of the region generate volatility connectedness to others.

The research reported in this paper can be extended in several directions in the future. First, it would be interesting to analyze how the return and volatility connectedness across several asset classes (stocks, foreign exchange, sovereign bonds and sovereign credit default swaps (CDS)) and countries have evolved since the early 2000s. Such an analysis would enable us to understand how much of the financial connectedness in the region is due to developments that originated in the region and how much is due to developments in the global economy. Along with the connectedness of financial markets in the region, it would also be quite relevant to study the macroeconomic connectedness of the region's economies.

References

Acharya, V.; L. Pedersen; T. Philippe and M. Richardson, (2010), "Measuring Systemic Risk," Manuscript, Stern School, New York University.

Adrian, T. and M. K. Brunnermeier, (2016), "CoVaR," *American Economic Review*, 106, pp. 1705–1741.

Alizadeh, S.; M. W. Brandt, and F. X. Diebold, (2002), "Range-based Estimation of Stochastic Volatility Models," *Journal of Finance*, 57, pp. 1047–1091.

Barigozzi, M. and C. Brownlees, (2013), "NETS: Network Estimation of Time Series," Manuscript, Universitat Pampeu Fabra and LSE.

Black, L.; R. Correa; X. Huang and H. Zhou, (2013), "The Systemic Risk of European Banks during the Financial and Sovereign Debt Crises," Manuscript, Federal Reserve Board, Washington, D.C.

Demirer, M.; F. X. Diebold; L. Liu and K. Yilmaz, (2017), "Estimating Global Bank Network Connectedness," NBER Working Papers 23140, National Bureau of Economic Research, Inc.

Diebold, F.X. and K. Yilmaz, (2012), "Better to Give than to Receive: Predictive Measurement of Volatility Spillovers," *International Journal of Forecasting*, 28, pp. 57–66.

Diebold, F.X. and K. Yilmaz, (2014), "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms," *Journal of Econometrics*, 182, pp. 119– 134.

Diebold, F.X. and K. Yilmaz, (2015), *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*, Oxford University Press.

Dungey, M.; M. Luciani and D. Veredas, (2013), "Googling SIFIs," Manuscript, ECARES, Free Universit´e libre de Bruxelles.

Engle, R.F. and B.T. Kelly, (2012), "Dynamic Equicorrelation," *Journal of Business and Economic Statistics*, 30, pp. 212–228.

Furman, Y., (2014a), "VAR Estimation with the Adaptive Elastic Net," *SSRN Working Paper*.

Furman, Y., (2014b), "Wide Volatility Spillover Networks," *SSRN Working Paper*.

Garman, M. B. and M. J. Klass, (1980), "On the Estimation of Security Price Volatilities From Historical Data," *Journal of Business*, 53, pp. 67–78.

Jacomy, M.; S. Heymann; T. Venturini and M. Bastian, (2014), "ForceAtlas2, A Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software," *PLoS ONE*, 9, Available at: www.plosone.org

Karaca, M. F. and K. Yilmaz, (2016), "Volatility Connectedness and Systemic Risk in the Insurance Industry," Manuscript, Koç University.

Koop, G.; M. H. Pesaran and S. M. Potter, (1996), "Impulse Response Analysis in Nonlinear Multivariate Models," *Journal of Econometrics*, 74, pp. 119–147.

Pesaran, H. H. and Y. Shin, (1998), "Generalized Impulse Response Analysis in Linear Multivariate Models," *Economics Letters*, 58, pp. 17–29.

Yilmaz, K., (2015), "Developing A Measure of Systemic Risk for European Banks," Manuscript, Koç University.

Zou, H. and T. Hastie, (2005), "Regularization and Variable Selection via the Elastic Net," *Journal of the Royal Statistical Society, Series B (Statistical Methodology)*, 67, pp. 301–320.

Appendix

A Dynamic Net Volatility Connectedness Across Banks

Figure A1
Indonesia and South Korea

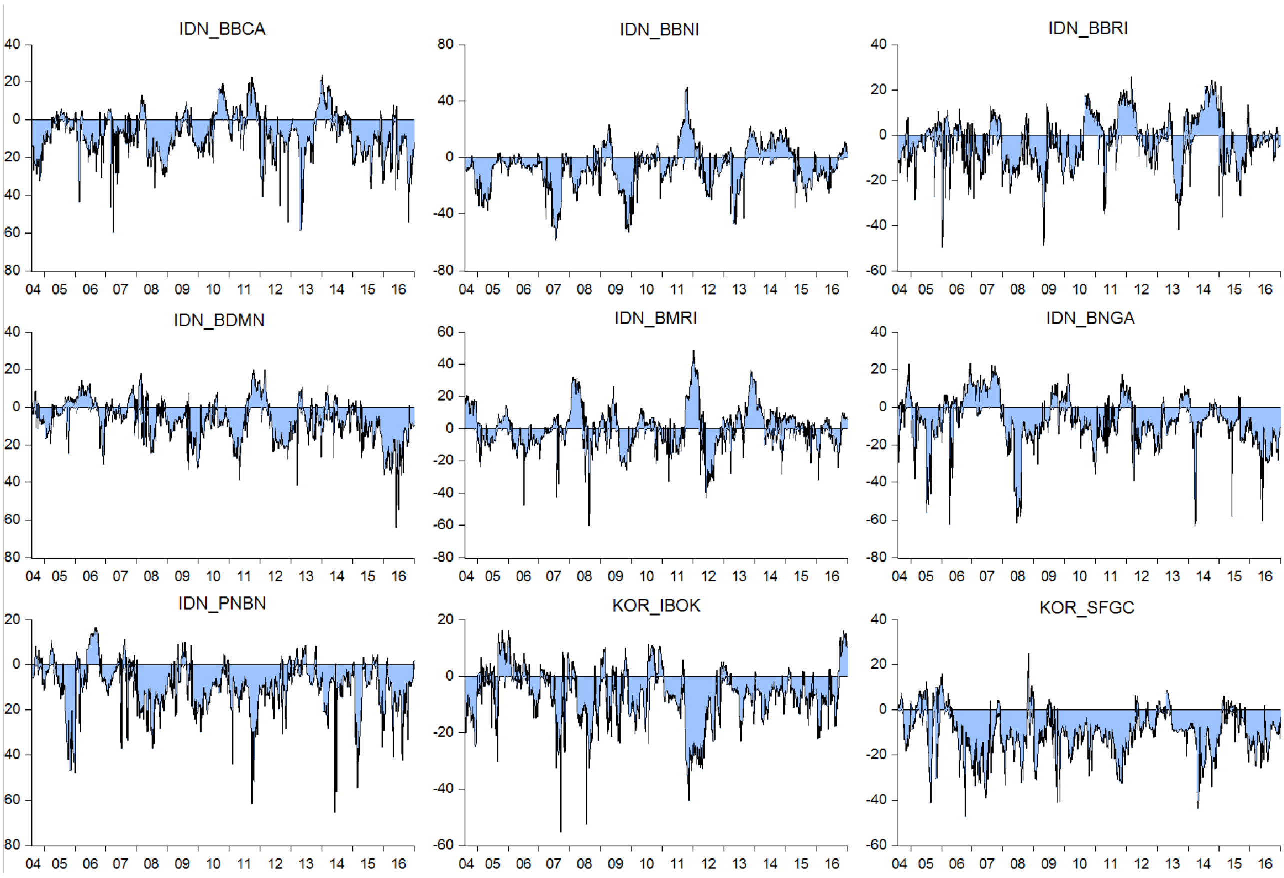


Figure A2
India

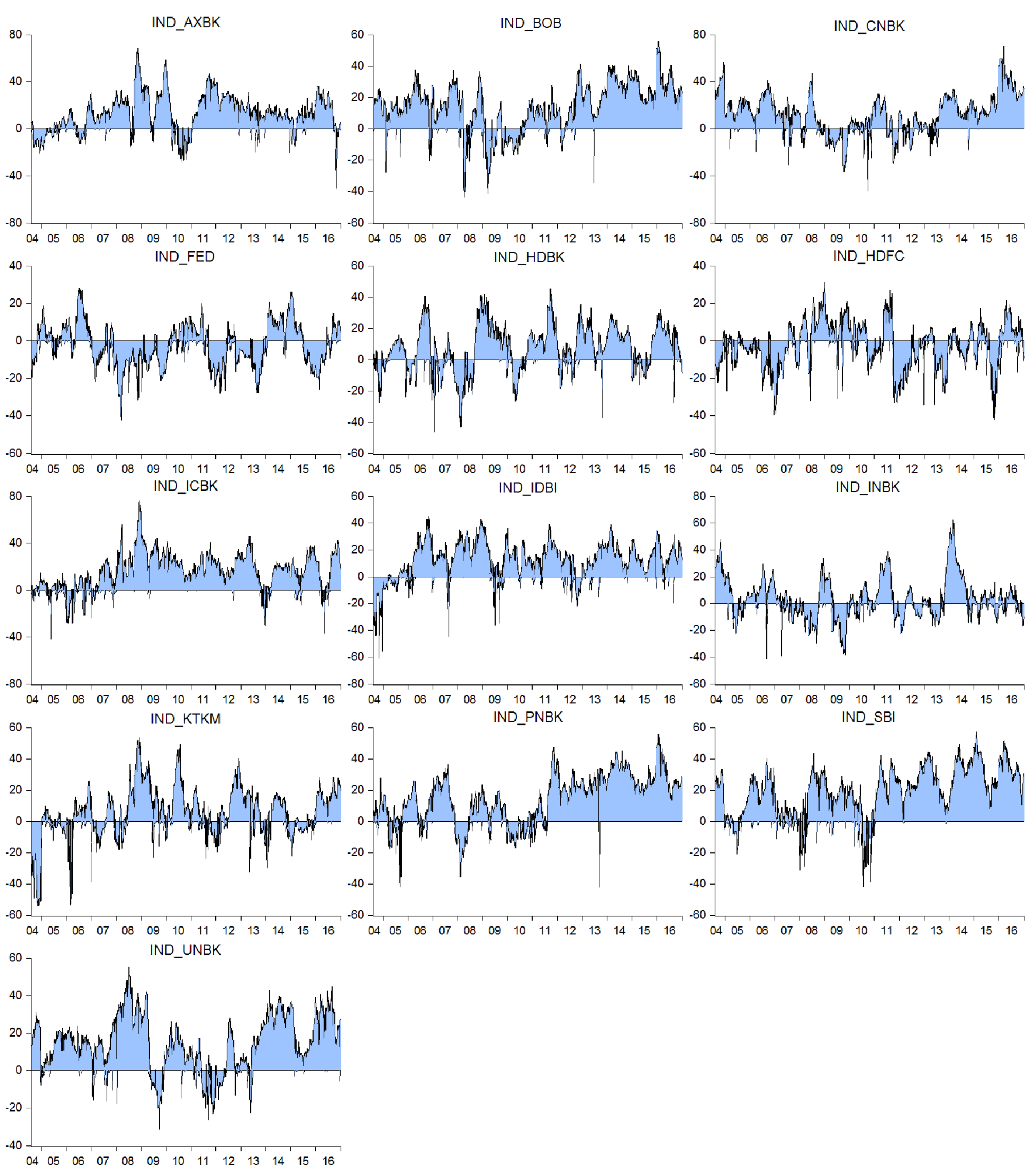


Figure A3
China, Hong Kong, the Philippines and Singapore

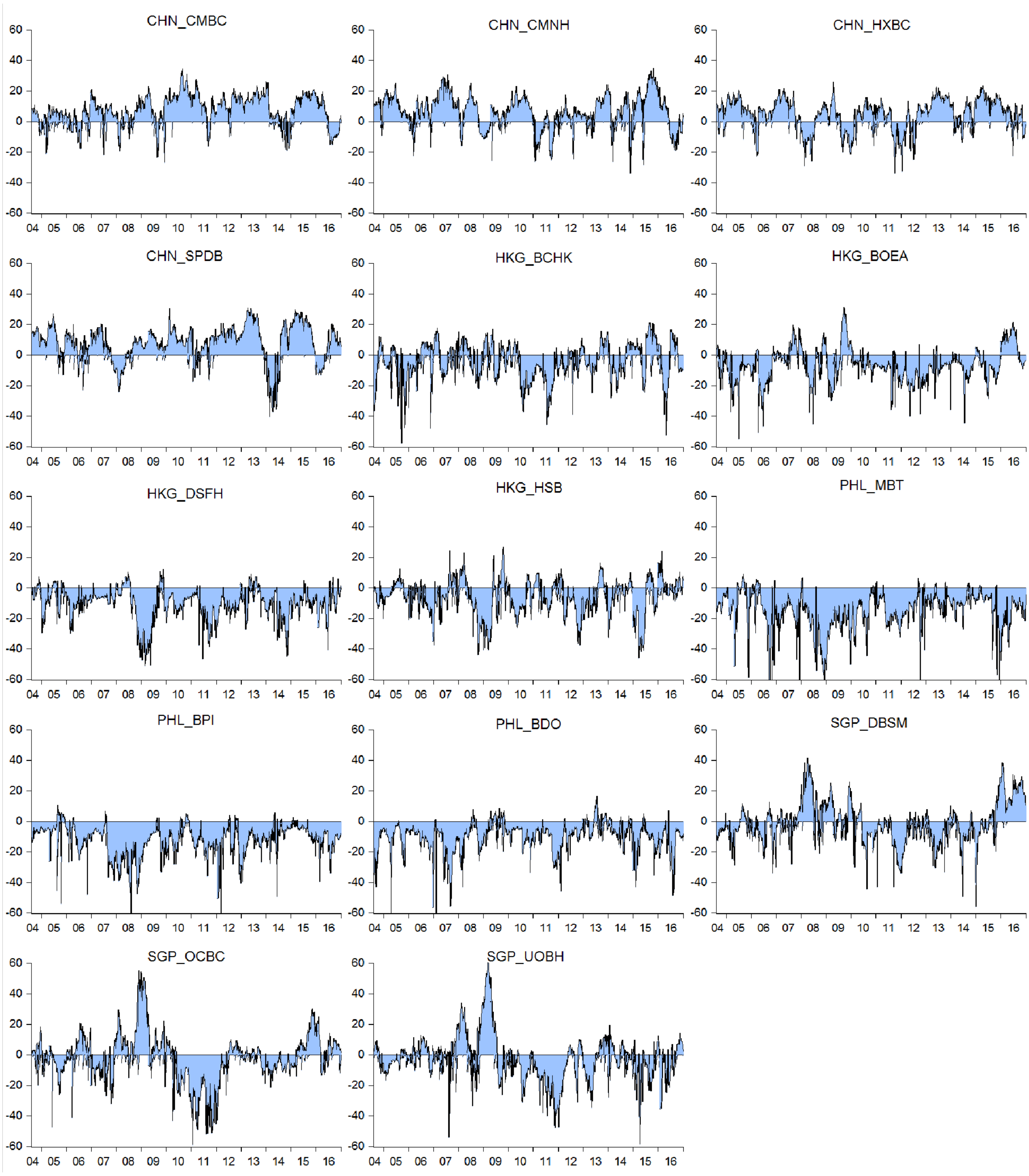


Figure A4
Malaysia

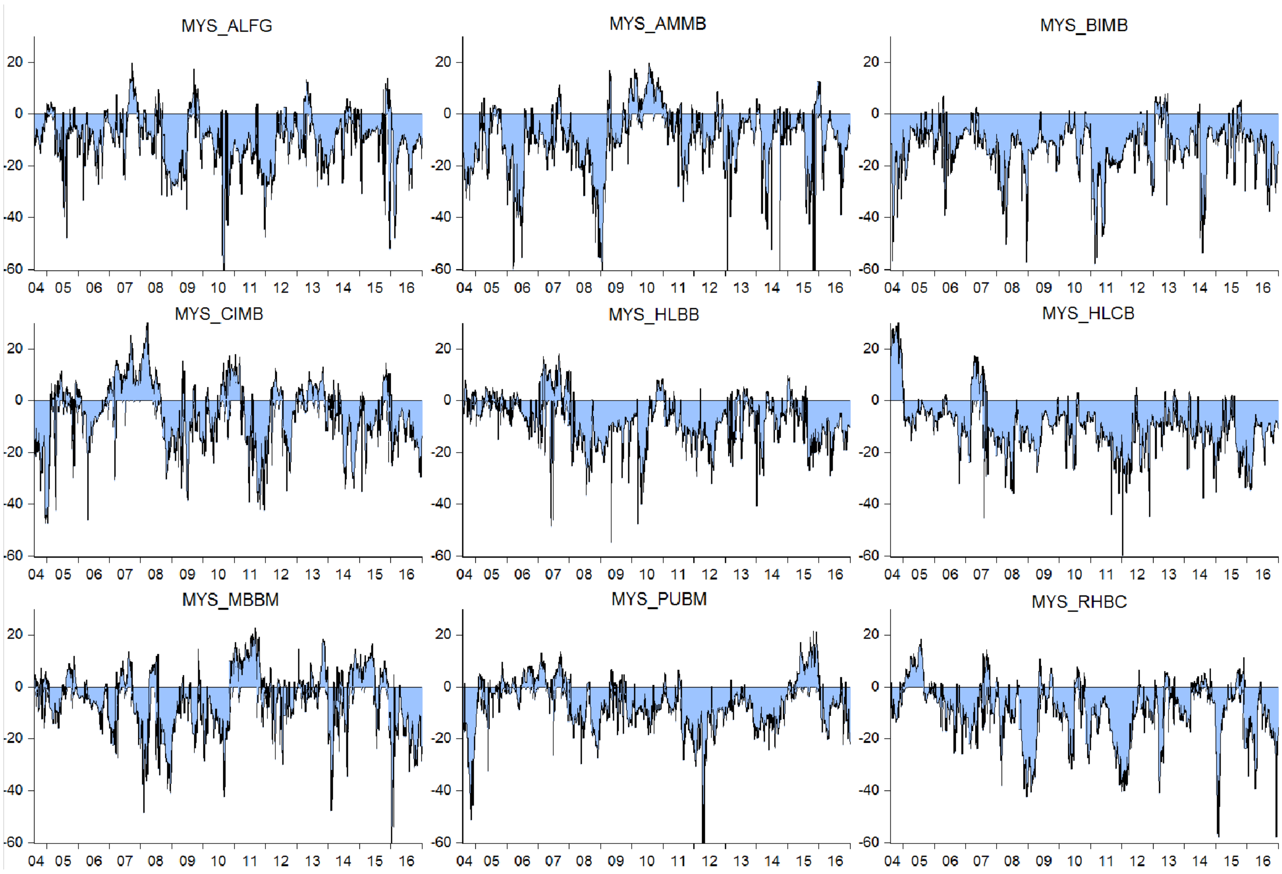


Figure A5
Chinese Taipei

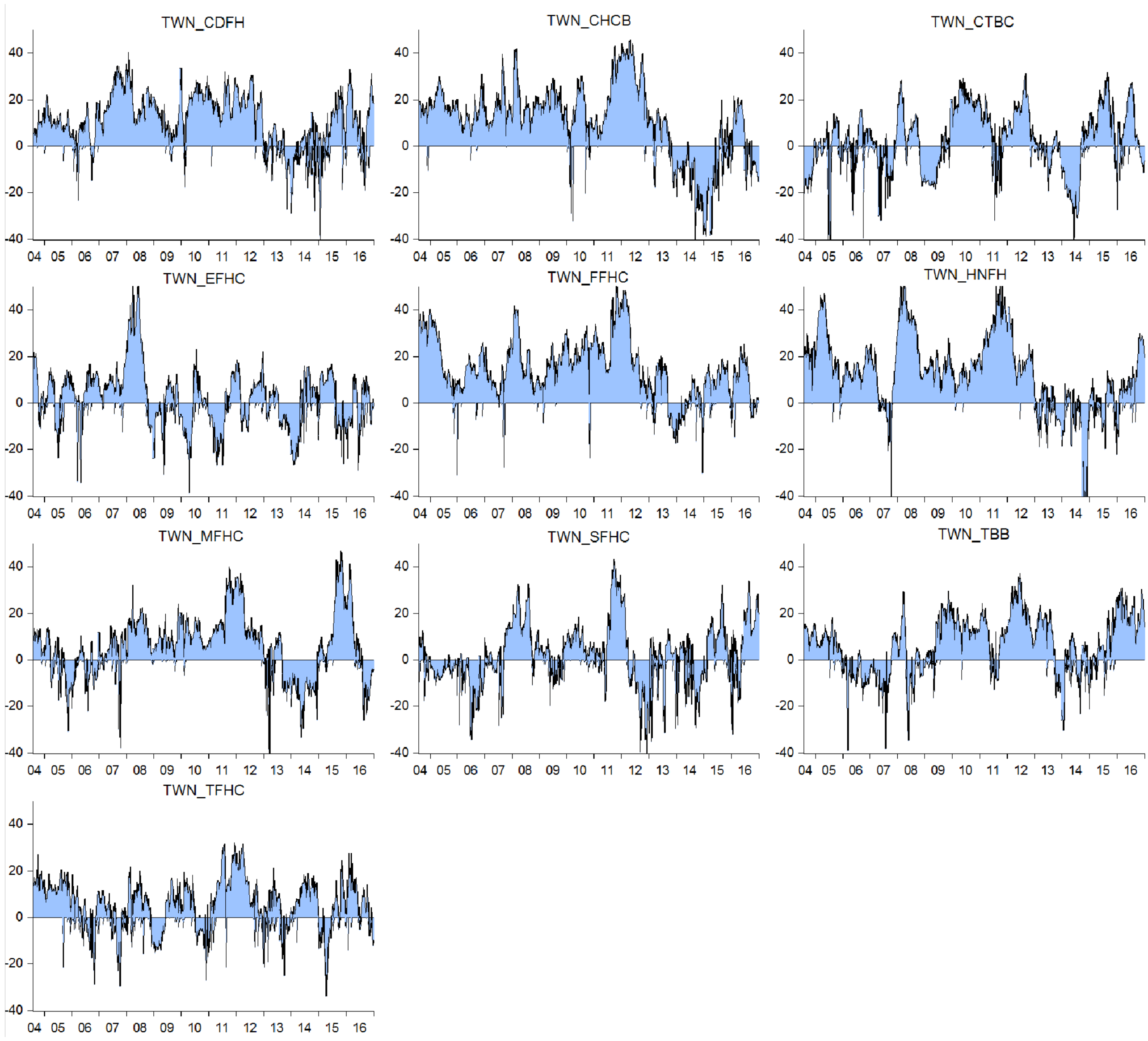


Figure A6
Thailand