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Intra-Regional Integration in the European and Asian Stock Markets

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In this study, we analyze the degree of intra-regional integration in European and Asian stock markets. We first use the methods of wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (WMCC) to examine the multiscale correlations of stock returns in the two regions. Then, we estimate the Diebold and Yilmaz spillover index for the stock returns and their wavelet details at each scale. The results indicate that the integration of European stock returns is stronger than that of Asian stock returns at every time horizons. They also indicate that France is the primary contributors to stock market integration in the eurozone, while Hong Kong and Singapore assume similar roles in Asia.

Keywords stock market, intra-regional integration, wavelet multiple correlation, wavelet multiple cross-correlation, spillover index,

1 Introduction

Economic integration is a popular topic for economists, especially after several recent financial crises. Therefore, stock market integration has long been a hot research topic. In this area, the integration of European stock markets is always mentioned, as no region can do better than the European Union (EU) in this regard. EU membership leads to increasing economic integration between European countries (Bekaert et al., 2013).

Pascual (2003) examines long-run co-movements in the stock markets of the UK, France, and Germany using co-integration approaches and finds results suggesting that the stock prices in the UK and France became important in explaining French stock price changes. Büttner and

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Hayo (2011) analyze the determinants of stock market integration among EU member states. They find that interest rate spreads, business cycles, and the size of the relative and absolute market capitalization are significant factors in explaining the increased stock market integration. Although the research subjects are all European countries, dividing the member states into groups reveals different degrees of stock market integration. For example, the Central European stock markets are the most integrated (Horvath and Petrovski, 2013). As an emerging research technology, prior studies apply the wavelet method to examines the financial topics (e.g., Madaleno and Pinho, 2012; Aloui and Hkiri, 2014; Cai et al., 2017; Reboredo et al., 2017; Kang et al., 2019). Dewandaru et al. (2016) analyze the integration of EU member stock markets by applying the continuous wavelet transform, and Fernández-Macho (2012) proposes wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (WMCC) to study the relationships among the European stock markets, and show that France's stock market is a potential leader.

In recent years, a growing number of studies examine the integration among Asian stock markets. Tai (2007) finds that the stock markets of India, Korea, Malaysia, the Philippines, and Thailand are fully integrated, and the relationship is dynamic. Moreover, the results also confirm the effect of liberalization on integration, and Arouri and Foulquier (2012) draw similar conclusions. Some researchers employ the panel unit root test, panel co-integration test, and detrended cross-correlation analysis to explore the increasing integration of Asian stock markets (e.g., Mohti et al., 2019; Lee, 2019). Wu (2019) applies the Diebold-Yilmaz (DY) spillover index (Diebold and Yilmaz, 2009, 2012, 2015) to study the integration among the East and Southeast Asian stock markets. The results suggest that the Chinese, Hong Kong, and Singaporean markets are always the most critical connectedness contributors before and after filtering the global effects.

In this study, we apply the methods proposed by Fernández-Macho (2012) and Diebold and Yilmaz (2009, 2012, 2015) to compare the degree of intra-regional stock market integration between Europe and Asia. To our best knowledge, this study is the first attempt to apply both the WMC/WMCC and DY spillover methods to analyze the degree of integration between the European and Asian stock markets. By doing so, we can compare the intra-regional stock return correlations and the connectedness between the two regions over different time horizons. We can also identify the primary contributor to the intra-regional integration, which acts as a potential leader or follower.

The remainder of this paper proceeds as follows. Section 2 outlines the methodology and describes the data, while Section 3 presents the empirical results. Finally, Section 4 provides our conclusions.

2 Methodology and Data

2.1 Discrete wavelet transform

We apply discrete wavelet transform (DWT) to a time series of stock markets returns to obtain wavelet and scaling coefficients, as well as wavelet details and smooths. Specifically, we use a modified version of DWT known as the maximal overlap DWT (MODWT), which we compute using the pyramid algorithm proposed by Percival and Walden (2000)[1].

We use multiresolution analysis (MRA) to decompose the time series of European and Asian stock market returns into parts corresponding to the variation in the series on different scales. For a partial DWT of level J_0, the MRA is

$$X = \sum_{j=1}^{J_0} D_j + S_{J_0}, \quad (1)$$

where D_j denotes an N-dimensional vector whose element $D_{j,t}$ is the j^{th}-level wavelet detail corresponding to the scale $\lambda_j = 2^{j-1}$ and S_{J_0} denotes an N-dimensional vector whose element $S_{J_0,t}$ is the J_0^{th}-level smooth corresponding to the scale $\lambda_{J_0} = 2^{J_0}$. Correspondingly, $D_{J,t}$ represents the variation of stock market returns over a $2^j - 2^{j+1}$ day horizon, while $S_{j,t}$ represents the trend obtained after removing the sum of $D_{j,t}$ to the j^{th} level from the series.

2.2 WMC and WMCC

Let $W_{jt} = (w_{1jt}, w_{2jt}..., w_{njt})$ be the vector of the j^{th}-level wavelet details obtained by applying the MODWT to each time series. Fernández-Macho (2012) define the WMC as a single set of multiscale correlations calculated from the vector of the time series as follows.[2] At each scale (λ_j), we calculate the square root of the regression coefficient of determination, denoted by R_i^2, in the linear combination of the wavelet coefficients w_{ijt}, $i = 1, ..., n$, for which such R_i^2 is the maximum. The R_i^2 corresponding to the regression of variable z_i on a set of regressors $\{z_k, k \neq i\}$ is $R_i^2 = 1 - 1/\rho^{ii}$, where ρ^{ii} is the i^{th} diagonal element of the inverse of the correlation matrix. Therefore, the WMC at scale λ_j, denoted by $\varphi_X(\lambda_j)$, is

$$\varphi_X(\lambda_j) = \sqrt{1 - \frac{1}{maxdiag P_j^{-1}}}, \quad (2)$$

where P_j is the $n \times n$ correlation matrix of W_{jt}, and the max diag(.) operator selects the largest element in the diagonal of the argument. Since we can show that R_i^2 is equal to the squared correlations between the observed and fitted values of z_i selected as the criterion variable at each scale, we can also rewrite the WMC as

$$\varphi_X(\lambda_j)=Corr(w_{ijt},\ \hat{w}_{ijt})=\frac{Cov(w_{ijt},\ \hat{w}_{ijt})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt})}}, \tag{3}$$

where we choose w_{ij} to maximize $\varphi_X(\lambda_j)$ and $\hat{w}_{ij}$ is the fitted value in the regression of w_{ij} on the rest of wavelet coeffcients at scale λ_j. Likewise, for a lag order of τ between the observed and fitted values of the selected z_i, the WMCC is

$$\varphi_{X,\tau}(\lambda_j)=Corr(w_{ijt},\ \hat{w}_{ijt+\tau})=\frac{Cov(w_{ijt},\ \hat{w}_{ijt+\tau})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt+\tau})}}. \tag{4}$$

We can decompose the wavelet variances and covariances as

$$Cov(w_{ijt},\ \hat{w}_{ijt})=\bar{\gamma}_j=\frac{1}{T_j}\sum_{t=L_j-1}^{T-1}w_{ijt}\hat{w}_{ijt}, \tag{5}$$

$$Var(w_{ijt})=\bar{\delta}_j^2=\frac{1}{T_j}\sum_{t=L_j-1}^{T-1}w_{ijt}^2, \tag{6}$$

$$Var(\hat{w}_{ijt})=\bar{\xi}_j^2=\frac{1}{T_j}\sum_{t=L_j-1}^{T-1}\hat{w}_{ijt}^2, \tag{7}$$

where $T_j=T-L_j+1$ is the number of coefficients unaffected by the boundary conditions, and $L_j=(2^j-1)(L-1)+1$ is the number of wavelet coefficients affected by the boundary associated with a wavelet filter of length L and scale λ_j.

Similarly, we can calculate a consistent estimator of the WMCC as

$$\varphi_{X,r}(\lambda_j)=Corr(w_{ijt},\ \hat{w}_{ijt+r})=\frac{Cov(\omega_{ijt},\ \hat{\omega}_{ijt+r})}{\sqrt{Var(\omega_{ijt})Var(\hat{\omega}_{ijt+r})}}. \tag{8}$$

Thus, if the $\hat{\varphi}_{X,r}(\lambda_j)$ is the sample wavelet correlation obtained for (1), then

$$\tilde{z}_j\sim{}^aFN(z_j,\ (T/2^j)^{-1}), \tag{9}$$

where $z_j=arctanh(\varphi_X(\lambda_j))$, $\tilde{z}_j=arctanh(\tilde{\varphi}_X(\lambda_j))$, and FN represents a folded normal distribution. The confidence interval for the sample of wavelet correlation coefficients is

$$CI_{1-\alpha}(\varphi_{X,\tau}(\lambda_j))=\tan h[\tilde{z}_j\pm\phi_{1-\alpha/2}^{-1}/\sqrt{T/2^j-3}]. \tag{10}$$

2.3 DY spillover index

We next estimate the DY spillover index (Diebold and Yilmaz, 2009, 2012, 2015)[3]. Diebold and Yilmaz (2009) first proposed the DY spillover index based on the Cholesky factor identification of a VAR that results in a variance decomposition that depends on the variable ordering. Then, by exploiting the generalized VAR model of Koop et al. (1996) and Pesaran and Shin (1998), (KPSS hereinafter), Diebold and Yilmaz (2012) extend the DY spillover index to measure the degree and direction of spillovers between financial markets independent of the causal variable ordering. A larger index value suggests a higher degree of spillover, implying that unanticipated movements in one variable are more likely to affect the other examined variables.

Following Diebold and Yilmaz (2009, 2012, 2015), we build a VAR(p) model as follows:

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t, \tag{12}$$

where Y_t is a vector of size N, which contains the original series or the wavelet details of the stock returns at time t, and $\varepsilon_t \sim iid(0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average representation is $Y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrices A_i obey the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$.

We can denote the KPPS H-step-ahead forecast-error variance decomposition by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \tag{13}$$

where $H = 1, 2, \ldots$, 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 e_i is the selection vector, with one as the i^{th} element and zeros otherwise. We normalize each entry in the variance decomposition matrix by the row sum:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{14}$$

Then, the TOTAL spillover index can be constructed as follows:

$$S^{g}(H) = \frac{\sum_{i=1,\, i \neq j}^{N} \sum_{j=1,\, j \neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,\, j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{i=1,\, i \neq j}^{N} \sum_{j=1,\, j \neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100, \tag{15}$$

which measures the contribution of the stock return shock spillover across all stock markets to the total forecast error variance. In other words, the index measures the system-wide connectedness of stock markets.

We measure the directional spillovers received by stock i from all other stocks using the FROM spillover index, defined as

$$S_{i\cdot}^{g}(H) = \frac{\sum_{j=1,\, j \neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,\, j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{j=1,\, j \neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100. \tag{16}$$

Likewise, we measure the directional spillovers transmitted by stock i to all other stocks using the TO spillover index defined as

$$S_{\cdot i}^{g}(H) = \frac{\sum_{j=1,\, j \neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,\, j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \cdot 100 = \frac{\sum_{j=1,\, j \neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \cdot 100. \tag{17}$$

By definition, the sum of each stock FROM spillover index is equivalent to the sum of each stock TO spillover index, which, in turn equals the TOTAL spillover index

$$\sum_{i=1}^{N} S_{i\cdot}^{g}(H) = \sum_{i=1}^{N} S_{\cdot i}^{g}(H) = S^{g}(H). \tag{18}$$

Finally, we obtain the NET spillover index from stock i to all other stocks using

$$S_i^q(H) = S_{\cdot i}^q(H) - S_{i\cdot}^q(H). \quad (19)$$

2.4 Data

Our data set spans from November 30, 2000, to December 1, 2019. We examine a group of European (eurozone) stock markets, which include Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Ireland (IE), Italy (IT), the Netherlands (NL), and Portugal (PT), and a group of Asian stock markets, which include China (CN), Chinese Hong Kong (HK), Indonesia (ID), Japan (JP), Korea (KR), Malaysia (MY), the Philippines (PH), Singapore (SG), Thailand (TH), and Taiwan Province of China (TW).

We measure stock returns as follows:

$$RE_{i,t} = (\log x_{i,t} - \log x_{i,t-1}) \times 100, \quad (20)$$

where $x_{i,t}$ is the price of stock i at time t. Thus, the data range of stock returns is from December 1, 2000, to December 1, 2019. We download the stock data from Bloomberg as the MSCI stock price. We report the summary statistics of the stock returns in Table 1.[4)]

Table 1. Summary Statistics

	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
Mean	0.01	0.00	0.00	0.00	−0.01	0.00	−0.01	−0.01	0.01	−0.01
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	13.53	10.27	11.80	15.34	17.41	12.05	13.19	12.87	10.92	11.16
Minimum	−12.04	−14.71	−9.35	−15.61	−20.57	−11.28	−19.20	−15.26	−11.23	−12.75
Std.Dev.	1.45	1.23	1.32	1.40	1.77	1.29	1.47	1.39	1.23	1.18
Skewness	−0.26	−0.47	−0.11	−0.11	−0.43	−0.07	−0.85	−0.25	−0.19	−0.22
Kurtosis	11.37	11.52	7.87	11.63	12.70	9.90	15.05	10.20	10.31	9.30
	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
Mean	0.01	0.01	0.02	0.00	0.01	0.01	0.01	0.01	0.02	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	14.03	10.47	15.23	12.19	21.34	5.94	22.02	8.52	10.27	8.01
Minimum	−12.84	−12.57	−19.93	−9.59	−18.60	−11.25	−14.37	−9.59	−18.11	−10.94
Std.Dev.	1.48	1.10	1.64	1.16	1.61	0.84	1.25	1.07	1.35	1.28
Skewness	−0.02	−0.34	−0.49	−0.19	−0.37	−0.49	0.73	−0.25	−0.56	−0.17
Kurtosis	9.33	11.00	12.25	7.50	15.19	11.33	25.49	8.30	12.63	5.53

Figure 1. Wavelet Multiple Correlations (WMC): European Stock Markets

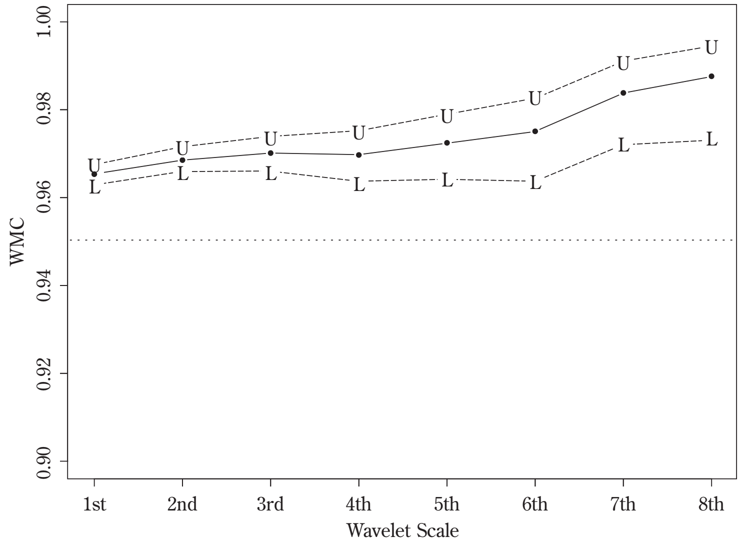
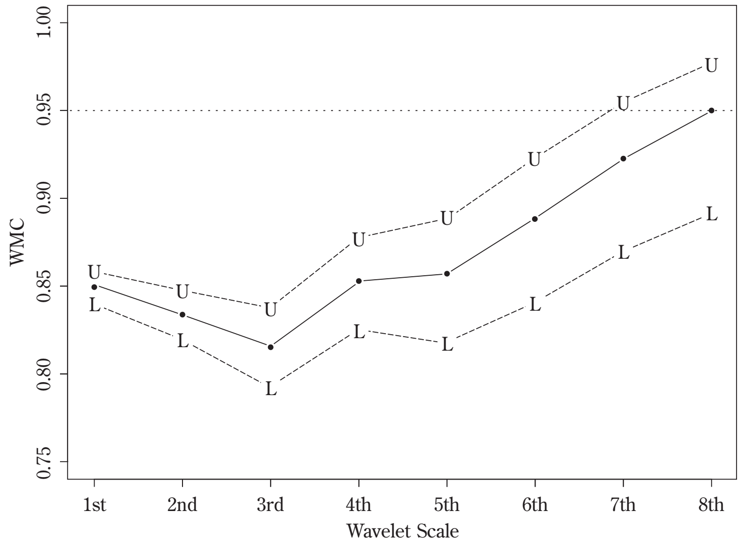


Figure 2. Wavelet Multiple Correlations (WMC): Asian Stock Markets

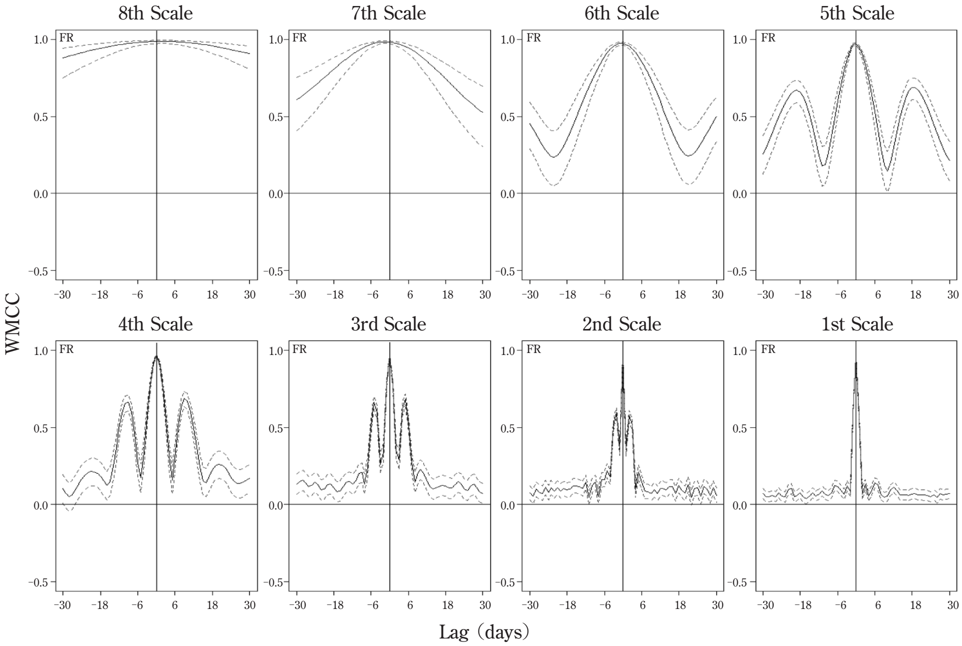


3 Empirical Results

3.1 WMC and WMCC

In this section, we apply the MODWT method with a Daubechies least asymmetric (LA) wavelet filter of length $L=8$ to derive the WMC and WMCC. Figures 1 and 2 show the WMC

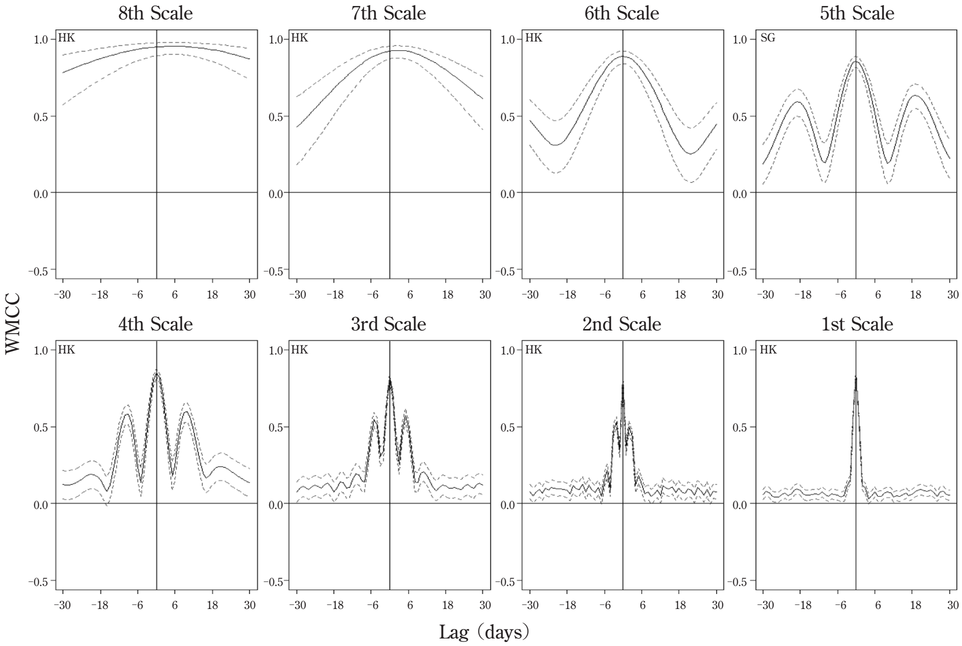
Figure 3. Wavelet Multiple Cross-Correlations (WMCC): European Stock Markets



of European and Asian stock returns, respectively, for each scale up to the 8th scale (λ_8). The dotted lines correspond to the upper and lower bounds of the 95% confidence interval.[5)] The figures show that the WMCs of the two stock returns series tends to increase with the scale; thus, the time horizon grows, even though the WMCs of the Asian stock returns declines from the 1st to the 3rd scale. More importantly, the intra-regional return correlation of European stock markets is stronger than the Asian stock markets is at any time horizon. Even the largest WMC of the Asian stock returns, which is 0.950 at the 8th scale (see the horizontal dotted line), is still less than the smallest WMC of the European stock returns, which is 0.965 at the 1st scale. However, we emphasize that the intra-regional return correlation of the Asian stock markets exceeds 0.8 at all scales, indicating a fairly high level of correlation.

Figure 3 shows the WMCC of the European stock returns, with leads and lags up to 30 days. The dotted lines correspond to the upper and lower bounds of the 95% confidence interval. The figures illustrate that almost all WMCCs appear significant at all leads and lags for all levels, and the WMCCs tend to increase as the time horizon gets longer, which is consistent with the WMC results. The upper-left corner signals that the FR acts as potential leader/follower for the other markets. Since there is no obvious asymmetry observed in the plots of WMCCs, it is not clear whether FR tends to lead or follow the other markets.

Figure 4. Wavelet Multiple Cross-Correlations (WMCC): Asian Stock Markets



In Figure 4, we present the WMCCs of the Asian stock returns. In this group, HK is a potential market leader or follower for the other Asian stock markets at almost all scales except the 5^{th} scale, at which Singapore (SG) is the potential leader/follower. Since there is no obvious asymmetry observed in the WMCC plots, it is not clear whether HK and SG tend to lead or follow the other markets.

To summarize, we find clear evidence that the intra-regional return correlation increases with the scale, and thus the time horizon grows in both the European and Asian stock markets. Although the Asian stock markets show weaker integration than do the European stock markets, the level of the correlation in Asian markets is rather high at all scales. We also find that the potential market leader or follower is FR in Europe, and HK and SG is the potential market leader in Asia. The latter result might reflect the fact that HK and SG serve as regional financial centers in Asia.

3. 2 DY spillover index

Following the benchmark specification of Diebold and Yilmaz (2015), we estimate the underlying VAR model with a lag order of 3 and derive the generalized variance decomposition using 12-day forecast horizons.[6]

Table 2 shows the TOTAL spillover index obtained from the original series and their wavelet details at each scale. The TOTAL spillover index measures the percentage share of forecast error variance from the spillovers from all other stocks. While the TOTAL spillover index tends to increase as the scale increases for Asian stock markets, there is no similar trend for the European stock markets. Most notably, the TOTAL spillover index of European stock returns is larger than the Asian stock returns is at every time scale. Even the largest TOTAL spillover index for the Asian stock markets, which is 75.38 at the 8^{th} scale, is smaller than the smallest TOTAL spillover index for the European stock markets, which is 81.07 at the 8^{th} scale. These results indicate that the system-wide return connectedness of European stock markets is stronger than the that of the Asian stock markets.

Table 2. Total Spillover Index of Stock Returns

TOTAL Spillover Index	European	Asian
Original Series	82.39	63.41
1^{st} Scale	81.93	59.55
2^{nd} Scale	82.50	63.22
3^{rd} Scale	82.84	66.05
4^{th} Scale	82.37	69.83
5^{th} Scale	82.23	69.79
6^{th} Scale	83.61	72.62
7^{th} Scale	82.61	71.71
8^{th} Scale	81.07	75.38

In Table 3, we present the breakdown of the TOTAL European stock returns spillover index by each stock's contribution. The TO spillover index measures the stock's contribution to the total spillover by transmitting shocks to the other stocks, while the FROM spillover index measures the stock's contribution to the TOTAL spillover by receiving shocks from the other stocks. As Equation (18) shows, the sum of the TO spillover index is equivalent to the sum of the FROM spillover index across all stocks, which in turn, equals the TOTAL spillover index. Based on the TO spillover index results, FR is the largest contributor to the TOTAL spillovers by transmitting shocks for all series. At the same time, the results of the FROM spillover index show that FR is the largest contributor to the TOTAL spillovers by receiving shocks for all series. Hence, FR seems to be the primary contributor, both as leader and follower, to the return connectedness in European stock markets. However, based on the NET spillover index results, we note that FR is also the largest contributor for all series, indicating that FR 's role as a leader surpasses

Table 3. Breakdown of Total European Stock Returns Spillover Index

Original Series	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	6.90	7.96	9.23	9.39	5.80	10.56	6.22	9.49	9.79	7.03
FROM	8.04	8.23	8.43	8.45	7.78	8.58	7.88	8.46	8.49	8.06
NET	−1.13	−0.27	0.81	0.94	−1.97	1.98	−1.66	1.03	1.30	−1.03

1st Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	7.23	7.57	8.60	9.58	5.67	10.51	6.46	9.55	9.74	7.04
FROM	7.78	8.32	8.44	8.41	7.80	8.57	7.70	8.40	8.47	8.04
NET	−0.55	−0.75	0.15	1.17	−2.14	1.94	−1.25	1.15	1.27	−1.00

2nd Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	7.21	7.73	9.24	9.13	6.09	10.67	5.83	9.42	9.96	7.21
FROM	8.05	8.23	8.45	8.48	7.75	8.56	8.03	8.49	8.48	7.97
NET	−0.85	−0.50	0.79	0.65	−1.66	2.10	−2.20	0.93	1.49	−0.76

3rd Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	6.52	8.47	9.44	9.44	5.83	10.30	7.16	9.49	9.50	6.71
FROM	8.33	8.19	8.47	8.45	7.89	8.62	7.73	8.50	8.55	8.12
NET	−1.81	0.28	0.96	0.99	−2.06	1.67	−0.57	0.99	0.96	−1.41

4st Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	6.26	7.77	10.71	9.62	6.92	10.98	5.70	9.33	8.98	6.09
FROM	8.30	8.23	8.32	8.41	7.46	8.53	7.92	8.50	8.61	8.09
NET	−2.05	−0.46	2.40	1.21	−0.54	2.46	−2.22	0.82	0.37	−2.00

5th Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	6.61	8.53	9.73	9.07	5.48	11.15	6.27	9.54	9.81	6.04
FROM	8.32	8.14	8.51	8.38	7.43	8.52	7.75	8.46	8.48	8.24
NET	−1.71	0.39	1.22	0.69	−1.95	2.62	−1.48	1.08	1.34	−2.20

6th Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	7.21	8.35	9.68	9.06	6.03	10.67	6.61	9.60	9.92	6.47
FROM	8.36	8.32	8.53	8.50	7.72	8.61	8.22	8.54	8.54	8.27
NET	−1.15	0.03	1.15	0.57	−1.69	2.06	−1.61	1.06	1.39	−1.81

7th Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	7.69	7.90	9.94	8.84	6.08	10.90	5.13	9.56	9.95	6.61
FROM	8.30	8.17	8.52	8.39	7.76	8.60	7.82	8.49	8.50	8.06
NET	−0.61	−0.27	1.42	0.45	−1.68	2.30	−2.68	1.07	1.46	−1.45

8th Scale	AT	BE	DE	ES	FI	FR	IE	IT	NL	PT
TO	7.15	7.54	9.72	8.66	4.30	11.03	6.56	9.22	9.96	6.91
FROM	8.05	8.05	8.45	8.25	7.09	8.57	7.81	8.36	8.45	8.01
NET	−0.90	−0.51	1.28	0.41	−2.79	2.46	−1.25	0.87	1.52	−1.10

its role as a follower.

Table 4 presents the breakdown of the TOTAL Asian stock returns spillover index. Based on the results of the TO spillover index, SG is the largest contributor in the Asian stock markets for six out of nine series, while HK is the largest contributor for the remaining three series. Note also that SG and HK are the largest contributors based on the FROM spillover index for seven series combined, while the KR is the largest contributor for two series. Therefore, considering the results of both the TO and FROM spillover indexes, SG and HK seem to be the primary contributors to the return connectedness in Asian stock markets. However, based on the NET spillover index results, SG is the largest contributor for six out of nine series, while HK is the largest contributor for the remining three series. Hence, the roles of SG and HK as leaders surpass their roles as followers.

In summary, the results for the TOTAL spillover index are broadly consistent with those of WMC, which indicate that the degree of integration in the Asian stock markets is lower than that in the European markets at every time horizon. The TO and FROM spillover index results indicate that the primary contributor to the system-wide return connectedness is FR in the European markets and SG and HK in the Asian markets. Furthermore, the NET spillover index results indicate that FR is a potential leader in the European markets, while SG and HK are the

Table 4. Breakdown of Total Asian Stock Returns Spillover Index

Original Series	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.42	8.85	4.98	4.14	7.65	5.46	3.71	9.12	5.23	5.84
FROM	7.08	7.17	5.82	5.57	6.84	6.13	5.39	7.11	5.97	6.32
NET	1.33	1.68	−0.84	−1.43	0.81	−0.66	−1.67	2.01	−0.74	−0.48

1st Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.12	8.41	4.22	4.81	6.95	5.29	3.60	7.33	4.45	6.37
FROM	7.08	7.16	5.72	4.71	6.52	5.75	4.27	7.29	5.63	5.42
NET	1.04	1.25	−1.50	0.11	0.43	−0.46	−0.67	0.04	−1.18	0.94

2nd Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.83	9.69	4.78	4.54	6.68	5.56	4.04	9.33	4.80	4.96
FROM	6.96	6.85	5.78	6.02	7.03	6.20	5.11	6.91	5.85	6.51
NET	1.87	2.84	−0.99	−1.48	−0.35	−0.64	−1.07	2.43	−1.05	−1.55

3rd Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.25	8.20	5.43	3.67	9.34	5.50	3.47	10.94	5.22	6.01
FROM	7.10	7.27	5.67	6.62	6.87	6.56	6.40	7.04	5.92	6.61
NET	1.16	0.93	−0.23	−2.94	2.47	−1.06	−2.94	3.90	−0.70	−0.60

4th Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.62	10.11	3.84	4.66	10.34	4.02	4.02	11.01	5.53	7.66
FROM	7.32	7.33	6.80	6.79	6.85	7.15	7.14	7.20	6.49	6.75
NET	1.31	2.78	−2.96	−2.13	3.48	−3.13	−3.12	3.81	−0.96	0.92

5th Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	9.51	8.88	4.32	5.27	9.24	4.67	4.28	10.38	6.36	6.87
FROM	7.35	7.42	6.66	6.42	7.32	6.78	6.91	7.47	6.50	6.96
NET	2.16	1.46	−2.34	−1.15	1.93	−2.12	−2.63	2.90	−0.14	−0.09

6th Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.87	9.10	4.43	5.74	10.14	4.79	5.49	10.40	5.55	8.10
FROM	7.49	7.50	6.93	6.83	7.68	6.95	7.14	7.66	7.18	7.26
NET	1.38	1.60	−2.49	−1.09	2.46	−2.16	−1.65	2.73	−1.63	0.85

7th Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	7.80	9.09	5.95	5.90	8.77	5.28	4.53	10.94	7.26	6.20
FROM	7.22	7.45	7.06	6.99	7.57	6.96	6.36	7.81	7.18	7.12
NET	0.58	1.64	−1.11	−1.08	1.20	−1.68	−1.83	3.13	0.08	−0.92

8th Scale	CN	HK	ID	JP	KR	MY	PH	SG	TH	TW
TO	8.00	9.73	7.00	4.61	8.38	7.52	6.00	9.11	7.67	7.35
FROM	7.66	8.03	7.36	6.91	7.78	7.62	6.99	7.90	7.52	7.61
NET	0.34	1.70	−0.36	−2.29	0.60	−0.10	−0.99	1.21	0.15	−0.26

potential leaders in the Asian markets.

4 Conclusion

This study analyzes the degree of intra-regional integration in the European and Asian stock markets. The WMC, WMCC, and DY spillover index results indicate that the integration of European stock market returns is stronger than that of the Asian stock market returns at every time horizon. In addition, both results indicate that France is the primary contributor to the stock market integration in the eurozone, while Chinese Hong Kong and Singapore assume similar roles in Asia. Furthermore, the NET spillover index results indicate that the roles of these three markets as leaders surpass their roles as followers. We believe that our study can make a valuable contribution to the literature by comparing the degree of stock market integration between two major regions and identifying the drivers of integration. Future work might further investigate the underlying factors that facilitate stock market integration in these regions.

Notes

1) We compute the MODWT using the R software "waveslim" package.
2) We compute the WMC and WMCC using the R software "wavemulcor" package.

3) We compute the DY spillover index using the R software "frequencyConnectedness" package.

4) We compute the skewness and kurtosis using the R software "moments" package.

5) The maximum decomposition level J_0 is given by $\log_2(T)$, which in our case, is 12. However, we set $J_0=8$ because the number of feasible wavelet coefficients gets critically small for high levels.

6) We conduct all analyses using R-packages, including "Wavelet" and "frequencyConnectedness".

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