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Abstract

Two integrated financial markets are generally subjected to common shocks revealing that commonalities in fundamentals drive the underlying return processes. In such a case, volatilities should share a long-run component although their transitory components might temporary diverge. Accordingly, we investigate financial integration in East Asian by analyzing the co-persistent nature of their integrated volatilities. Using recent fractional cointegration techniques, we find that volatilities of several markets converge in long-run to a common stochastic equilibrium. Our results reveal that a global integration process drives the most developed markets of the region, while no evidence of co-persistence appears between emerging markets.

Keywords: Integrated volatility, Co-persistence, Fractional Cointegration, East Asian Stock Markets, Financial Integration
JEL: G15, F36, C22

1. Introduction

Financial integration issue is closely related to cross-country links in stock markets and more precisely to the correlation of returns and volatility (see, e.g., Beckaert and Harvey , 1995). Given that volatility of stock markets reflects to a large extent the risk exposure of assets, we expect that existence of cross-market correlations should reveal common risk premium associated with an identical risk exposure. Accordingly, integrated stock markets are more likely to display greater correlation among their volatility processes because the source of risk is the same, while the opposite is true for segmented markets. Harvey (1995) argues that stock markets in emerging countries are more likely to be influenced by local events, suggesting a lower degree of financial integration, while developed markets

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are more likely to be tied through a global integration process because the risk exposures are likely influenced by global variables (see, also, Engle and Susmel , 1993). This issue has been widely investigated in the literature since many financial and regulatory activities (e.g. pricing of financial instruments, performance evaluation, risk hedging strategies and portfolio allocation) depend upon the perceived commonality in volatility movements. In this regard, understanding interrelations among closely related stock markets is crucial.

In this paper, we explore the presence of common stochastic trends among integrated volatilities of several Asian equity markets (Japan, Hong Kong, Singapore, Malaysia, Thailand, Indonesia, the Philippines) to assess the degree of financial integration in this area. We support that existence of long-run relationship between their integrated volatilities should reveal at least a partial financial integration while absence of commonalities should indicate segmented markets. Indeed, cross-border correlation in volatilities could exist throughout a common long-run component although the transitory components might temporary diverge. In such cases, stock markets are cointegrated, implying that the volatilities converge in the long run and respond in similar ways to shocks. This entails that volatilities are driven in the long run by a common information arrival process (i.e. the information events causing the volatility are the same) that should reflect commonalities in the market fundamentals (e.g. trade connections, similar economic and institutional structures and cultures). Considering the well documented influence of the US on Asian stock markets (see, e.g., Ng , 2000; Chuang et al. , 2007), we also include in our panel the Standard & Poor's 500 to test whether volatilities in these markets are cointegrated with the US stock market.

Previous empirical studies rely on numerous econometric approaches including among other, VAR and cointegration analysis, GARCH class of models or common-component approach (see, e.g., Yu et al. , 2010, for a survey of high-frequency integration measures). Since higher correlation between second moment of returns generally implies greater integration among stock markets and higher co-movement, constant and dynamic correlation analysis of conditional variance has been widely used to capture the extent to which the covariances with world or regional markets are relevant. For instance, Miyakoshi (2003) shows that the volatility of the Asian financial markets is influenced more by the Japanese market than by the US. Tai (2007) examines whether Asian emerging stock markets have become integrated into world capital markets and find full market integration after the official liberalization date,[2] while Chambert and Gibson (2008) find that Asian countries still remain segmented, even if the level of stock market integration has been trending upwards more recently. Yu et al. (2010) analyze stock markets correlation using dynamic conditional correlation model and find that all stock markets in Asia show increasing correlation with each other in the past year (see, also, Ng , 2000; Worthington and Higgs , 2004; Click and Plummer , 2005; Chuang et al. (2007); Beirne et al. , 2010; Abbas et al. , 2013; Lee , 2013).

[2]The author uses the official liberalization dates reported by the International Finance Corporation.

However, all aforementioned studies focus on short term correlation and, therefore, the transitory component of the variances and covariances. Accordingly, they neglect the persistent nature of volatility which is of importance regarding the possibility of long-run correlation. Our methodology employs recent fractional cointegration techniques and relies on the rank analysis as well as the regression-based analysis, accommodating in both cases the possible non-stationarity of the volatility processes. Considering that volatilities are persistent, the fractional cointegration is a convenient approach to capture the share of the volatility in both markets which has a common origin. The pioneer work of Bollerslev and Engle (1993) addresses this issue by extending the cointegration theory to conditional variance (they term this concept co-persistence). Li (2012) deals with some drawbacks of Bollerslev and Engle (1993) and find strong evidences of financial integration in European markets. However, the multivariate integrated GARCH framework of Bollerslev and Engle (1993) and Li (2012) implies a very strong hypothesis: the volatility process possesses a unit root.[3] Brunetti and Gilbert (2000) relax this assumption, considering long memory in conditional variance. [4] Ho and Zang (2012) study the financial integration of the Greater China through a varying-correlation fractionally integrated asymmetric power GARCH model. They extensively discuss the co-persistence issue although they do not test for the presence of common stochastic trends. Dao and Wolters (2008) investigate co-persistence through multivariate stochastic volatility model but assuming a unit root in volatility processes. They find evidence of common stochastic volatility trends in several developed East Asian stock markets. In a pure theoretical study, da Silva and Robinson (2008) relax the unit root assumption of Dao and Wolters (2008) and develop a bivariate long memory stochastic volatility model. Concerning integrated variance, the pioneer work of Andersen et al. (2003) provides an heuristic analysis of fractional cointegration among the volatility of three exchange rates and concludes in favor of no cointegration. In a recent study, Cassola and Morana (2010) study the common sources of volatility in the Euro Area money market interest rates.

In line with these studies, we investigate the presence of common stochastic trends among the integrated volatilities of several Asian stock markets. The extent to which emerging and developed markets in Asia are fractionally cointegrated is of importance for three reasons. First, the lack of commonality in the volatility processes (i.e. the absence of a common underlying trend) can emphasize the potential benefits of portfolio diversification, especially for investors who engage in volatility arbitrage on these markets. Second, intensified financial linkages in a world of high capital mobility may also generate the risk of volatility spillovers among closely related markets, but also undesirable macroeconomic effects (e.g. monetary expansion, inflationary pressures, real exchange rate appreciation).

[3]The presence of a unit root in the volatility stochastic process seems too extreme inasmuch as it implies permanent shifts to long-term volatility forecasts, which is theoretically implausible.

[4]See Figuerola-Ferretti and Gilbert (2008) for an application of the bivariate error correction mechanism FIGARCH model of Brunetti and Gilbert (2000). See also Bollerslev and Mikkelsen (1996) and Andersen et al. (2003) for a discussion about the long memory feature of the conditional and integrated variance.

Accordingly, if volatilities respond in similar ways to shocks, policymakers and regulators within the region may find an interest to achieve greater degree of financial cooperation to enhance regional financial stability.[5] Moreover, financial integration is theoretically related to the possibility of sharing country-specific output shocks, both in "good" and "bad" times, via the cross-ownership of equities. Therefore, financial integration would potentially benefit the region through consumption smoothing and risk sharing, facilitating the adjustment in the face of asymmetric shocks. From the perspective of Asian monetary integration, this would make the adoption of a common currency more desirable because financial market integration would act as an insurance mechanism, which is of great importance for the smooth functioning of a monetary union (see, e.g, de Grauwe , 2005).[6]

To anticipate our main conclusions, the preliminary analysis reveals that, in most cases, the pairwise volatility processes exhibit a common degree of persistence. We also find strong evidences of co-persistence between volatilities of developed markets, confirming that Hong Kong and Singapore enter into a global integration process. Conversely, we find only little evidences of cointegration in variance among Malaysia, the Philippines, Indonesia and Thailand equity markets, confirming that emerging markets remain segmented.

The remainder of the paper is laid out as follows. The Section 2 details the dataset and the strategy of estimation. The Section 3 discuss the results and their economic implications. Section 4 concludes the paper.

2. Fractional cointegration estimation and testing

2.1. The data

Over the last three decades, the Asian economies have emerged as a pole of economic growth. The opening up of additional channels for cross-border linkages has contributed to more interrelated economies, which in turn, has given rise to greater co-movements with world stock markets. For instance, Park and lee (2011) indicate that the Asian countries have attracted about 57% of total financial inflows to emerging market economies over the last two decades, as a result of financial deregulation and capital account liberalization. Chinn and Ito (2008) construct a *de jure* index of capital account openness, also called *KAOPEN*, and find that the Asian countries have reached a high level of financial openness compared to other groups of emerging countries, although the rate of financial opening slowed down in the aftermath of the 1997-98 crisis.

[5] The Asian governments have already embarked on several initiatives for regional financial cooperation in the aftermath of the 1997-98 crisis, including regional economic surveillance process (the Economic Review and Policy Dialog in May 2000), a liquidity support arrangement under the form of bilateral swaps (the Chiang Mai Initiative Multilateralized in 2009) and Asian bond markets developments (the Asian Bond Fund initiative of the Executive Meeting of East Asia Pacific Central Banks in 2003) However, it is generally argued that financial integration lags behind real integration, despite the political support toward greater financial cooperation (see, e.g., Kim and Lee , 2012).

[6] The other analytical benefits refer to the positive impact of capital flows on domestic investment and growth, the additional discipline on macroeconomic policies and the efficiency improvements of the banking sector (Agénor , 2003).

We concentrate our analysis on the national stock market index of seven Asian countries, including both developed and emerging markets: the Stock Exchange of Thailand (SET), the Straits Time Index of Singapore (STI), the Philippines Stock Exchange Index (PSEI), the Kuala Lumpur Composite Index (KLCI, Malaysia), the Jakarta Composite Index (JCI, Indonesia), the Hang Seng Index (HSI, Hong Kong) and the Nikkei 225 (NKY, Japan). Our data set cover the period January 1, 2000 to November 29, 2012, and the sample size is 3315.[7] Three of these markets are regarded as developed (Hong Kong, Japan and Singapore) while others are categorized as emerging (Indonesia, Malaysia, the Philippines and Thailand). Tokyo and Hong Kong are the two largest international financial centers in Asia in terms of market capitalization. Moreover, these two countries with Singapore are the more financially open economies in Asia according to the *KAOPEN* index of Chinn and Ito (2008) (see Table 1).[8] Finally, according to Click and Plummer (2005), the five most advanced members of the ASEAN (i.e. Singapore, Thailand, the Philippines, Indonesia and Malaysia) are the most likely candidates in Asia to foster financial cooperation and undertake measures to improve regional integration of financial markets.

Table 1: Stylized facts on Asian markets

	Mal.	Indo.	Thai.	Phil.	Sing.	HK	Jap.
Market cap. (2010)	408 689	360 388	277 731	157 320	647 226	2 711 316	3 827 774
KAOPEN (2011)	-1.168	-0.112	-1.168	-1.168	2.439	2.439	2.439

Notes: The domestic market capitalizations (in USD millions), extracted from the World Federation of Exchanges database, are those of the national stock market indexes included in our panel. *KAOPEN* is based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions*. According to Chinn and Ito (2008), *KAOPEN* This index takes on higher values the more open the country is to cross-border capital transactions.

These markets are likely to response in different ways to shocks depending on whether they are integrated with world or regional markets, that is the US or Japan (see Ng , 2000). To investigate the relative importance of the world's two largest stock markets on smaller Asian stock markets, we include the Standard & Poor's 500 (SPX) to our panel. Figs 1 and 2 reproduce the respective time paths of range-based volatility on the emerging and developed stock markets. Clearly, the volatilities represented on Fig 2 seem to be highly related when comparing with those of Fig 1.[9]

2.2. *Econometric framework*

Considering the stylized fact that shocks in volatility persist over time (see e.g. Berger et al. , 2009, for a discussion on the source of the volatility persistence), the cointegration techniques are useful to guard against the risk of spurious

[7] Data are obtained from Bloomberg.
[8] The MSCI and FTSE group classify Singapore and Hong Kong as developed markets.
[9] The turmoil of December 2006 for SET is due to the currency reserve requirement imposed by the government on foreign stock investments.

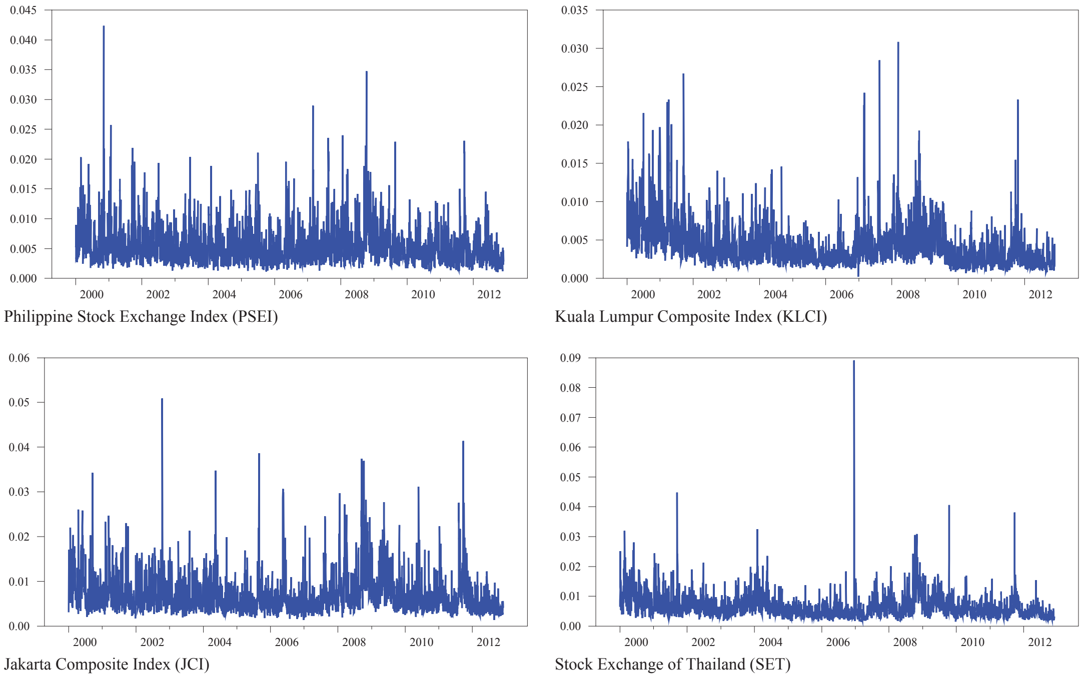

Figure 1: Daily range of emerging stock market indexes.

regression and investigate whether volatility processes share a common stochastic trend.[10] Indeed, cointegration is a powerful theory devoted to the analysis of long-run relationship. It states that a vector of p series, X_t, integrated of same orders, share $p - r$ common stochastic trends if there exists r linear combinations between the elements of X_t, having smaller orders of integration than X_t. The concept initiated by Granger (1981) does not restrict integration orders of X_t and the cointegrating errors to be integers. Accordingly, cointegration with real integration orders, termed fractional cointegration, has attracted a growing attention during the last decade and notably the interesting case where X_t is covariance-stationary but long-range dependent. Among others, recent contributions of Nielsen (2007), Robinson (2008) and Shimotsu (2012) can be listed concerning univariate case while Hualde and Robinson (2010) and Johansen and Nielsen (2012) treat the multivariate case. This concept of stationary fractional cointegration is particularly relevant in empirical finance in which volatility series are often found to be covariance-stationary but exhibit long memory (see e.g. Andersen et al. , 2003; Christensen and Nielsen , 2006). Nonetheless, there is no theoretical reason for the volatility process to be stationary. Using more appropriate techniques, Berger et al. (2009) and Frederiksen et al. (2012) produce estimates of the volatility persistence in the non-stationary region. Therefore,

[10]Indeed, this risk exist whether or not the time series are covariance stationary as long as their integration orders sum up to a value greater than 1/2 (see Tsay and Chung , 2000).

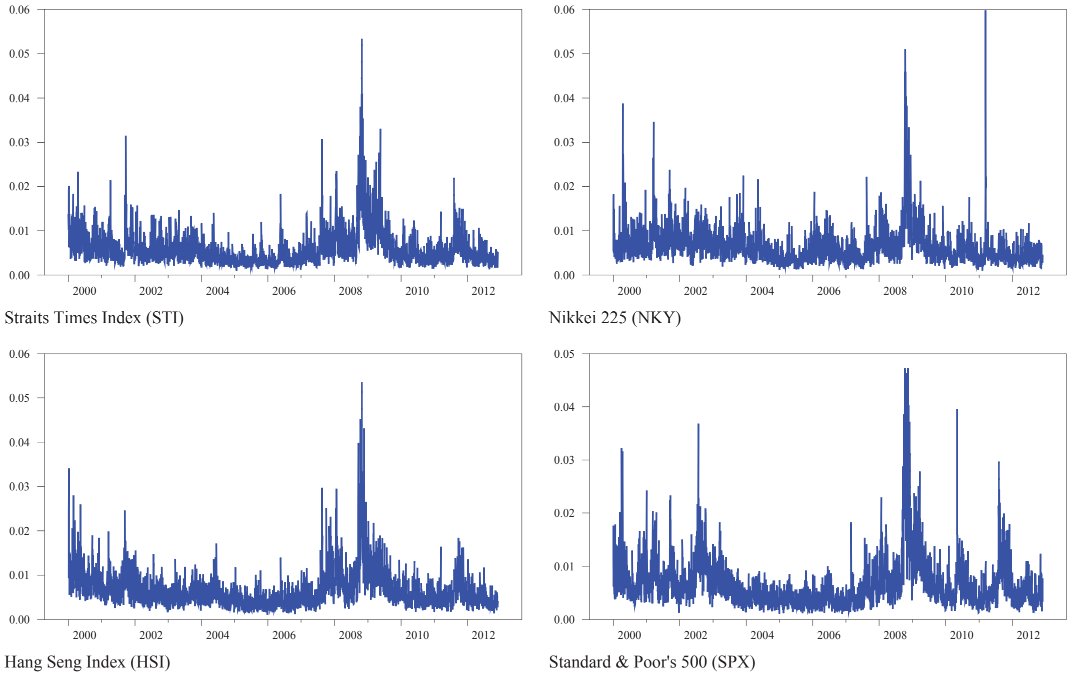

Figure 2: Daily range of developed stock market indexes.

we are interested by estimators of fractional cointegration able to assess both stationary and moderately non-stationary processes.

2.3. *Co-persistence model*

We consider a simple cointegration system to investigate pairwise long-run relationships between volatility of market a and b,

$$(1-L)^{\gamma}(r_{t,a}-\beta r_{t,b})=\varepsilon_{1t}, \qquad (1-L)^{\delta} r_{t,b}=\varepsilon_{2t}, \qquad t=1,2,...,n, \qquad a\neq b, \tag{1}$$

In Eq. (1), $\{r_{t,.}\}$ is the low frequency daily range defined by the difference between the highest ($h_{t,.}$) and the lowest ($l_{t,.}$) log security prices over a day [11]. Terms $(1-L)^{\delta}$ and $(1-L)^{\gamma}$ are the fractional filter, further denoted Δ^{δ} and Δ^{γ} respectively. Parameters δ captures the persistence nature of the two observed volatilities while parameter γ measures the persistence of the long-run residuals ε_{1t}. According to the cointegration theory, co-persistence occurs when the long-run coefficient β is non-null and the strength of the long-run relation, $\nu=\delta-\gamma$, is positive.

[11] Their is an extensive literature concerning realized volatility measures. In line with many studies, we support that the range-based volatility is a good proxy for the *true* volatility (see e.g. Martens and Van Dijk , 2007; Engle et al. , 2012).

2.4. *The strategy of estimation*

Fractional cointegration can generally be investigated following two different methodologies. The first is the so-called regression-based approach and requires to estimate the cointegrating vector(s), the integration orders of the regressor(s) and the cointegrating residuals. It has the advantage of providing accurate information concerning the strength of the long-run relationship. Nonetheless, it implies some difficulties in testing for cointegration when integration orders are not confined in a particular region of the parameter space. In such cases, there is little consensus on how to test for fractional cointegration. The second consists of estimating the cointegrating rank and does not imply any such requirement. However, it often requires tuning parameters that increases the sensitivity of the results and one can encounter some difficulties to obtain entirely conclusive results. To overcome these difficulties and to be more confident in the interpretation of the results, we adopt the following strategy: first, we test for the homogeneity of the integration orders δ_a and δ_b using an extended version of the Robinson and Yajima (2002)'s method that accommodates both stationarity and non-stationarity; second, we save the pairs for which $\delta_a = \delta_b$ and estimate their cointegrating rank by applying the rank estimator of Nielsen and Shimotsu (2007); third, we implement the regression-based approach by applying the exact local Whittle estimator of fractional cointegration proposed by Shimotsu (2012).[12]

All the aforementioned procedures operate in frequency domain and are semi-parametric thus focusing on a degenerating part of the periodogram around the origin. Accordingly, our approach is invariant to short-run dynamics and we are not concerned by misspecification issues. The later advantage has its counterpart since in consideration of the sensitivity of these procedure to the choice of the bandwidth, m, we have to be careful in interpreting the results. In this study, we are essentially concerned by the fact that bandwidth parameter must not tend very fast to ∞ with n to avoid higher frequency bias. This consideration is of importance because volatility is often subject to a perturbation term (see Frederiksen et al. , 2012), not modeled in our framework, which state the bandwidth requirement to $m = o(n^{2\delta/(1+2\delta)})$. In our case, we support that $m = \lfloor n^{0.5} \rfloor$ is reasonable considering both, this bandwidth requirement and the sample size $n = 3315$. Therefore, results are only reported for $m = \lfloor n^{0.5} \rfloor$ although several values for tuning parameters and bandwidths have been considered along the paper[13].

2.5. *Testing for equality of integration orders*

Testing for the equality of δ_a and δ_b is a necessary condition for $r_{t,a}$ and $r_{t,b}$ to be non-trivially cointegrated. Considering the null hypothesis of pairwise equality, $H_0 : \delta_a = \delta_*, a = 1, \ldots, p, p = 2$, Robinson and Yajima (2002) propose the following test statistic

[12] Nielsen and Frederiksen (2011) and de Truchis and Keddad (2013) employ a similar methodology applied to stationary and non-stationary data respectively.

[13] All unreported results are available upon request.

Table 2: 2S-ELW estimates of δ with $m = \lfloor n^k \rfloor$

k	SET	STI	PSEI	KLCI	JCI	HCI	NKY	SPX
0,4	0,457	0,473	0,257	0,682	0,180	0,584	0,478	0,605
0,5	0,373	0,531	0,248	0,402	0,311	0,676	0,425	0,586
0,6	0,451	0,602	0,262	0,399	0,366	0,657	0,597	0,605
0,7	0,363	0,557	0,281	0,363	0,340	0,535	0,474	0,620
0,8	0,362	0,455	0,304	0,397	0,387	0,430	0,433	0,509

$$\hat{T}_0 = m(S\hat{\delta}_{ab})' \left(S\frac{1}{4}\hat{D}^{-1}(\hat{G}\odot\hat{G})\hat{D}^{-1}S' + h(n)^2 I_{p-1} \right)^{-1} (S\hat{\delta}_{ab}), \qquad p = 2, \tag{2}$$

where $\hat{\delta}_{ab} = (\hat{\delta}_a, \hat{\delta}_b)'$, I_p is an identity matrix of dimension p, $\odot$ denotes the Hadamard product, $D = \text{diag}\{G_{11}, \ldots, G_{pp}\}$ and $S = [I_{p-1}; -\iota]$, with ι a $(p-1)$-vector of ones. $\hat{G}$ is the cross-spectral density matrix of residuals at zero-frequency. The tuning parameter $h(n)$ is chosen such as $h(n) = (\log n)^{-1}$, following Nielsen and Shimotsu (2007). Under the null hypothesis, $\hat{T}_0 \xrightarrow{d} \chi^2_{p-1}$ if r_t is not cointegrated and $\hat{T}_0 \xrightarrow{p} 0$ if r_t is cointegrated, with $r_t = (r_{t,a}, r_{t,b})'$.

Parameters $\hat{\delta}_a$, $\hat{\delta}_b$ and $\hat{G}$ are obtained from a multivariate version of the two-step exact local Whittle estimator (2S-ELW) of Shimotsu (2010)[14]. Table 2 reports the 2S-ELW estimates of persistence of each volatility for the bandwidth $m = \lfloor n^k \rfloor$, with $\lfloor . \rfloor$ the floor function and $k = \{0.4, 0.5, 0.6, 0.7, 0.8\}$. We observe that all long memory parameters are nor confined in a close interval neither regrouped in a precise region of the parameter space. Indeed, most of the volatilities are covariance stationary ($\delta < 0.5$) albeit in some cases series are moderately non-stationary ($\delta \geq 0.5$), encouraging us to consider an empirical strategy that accommodates both stationary and non-stationary cases.

2.6. *The rank analysis*

The test of Robinson and Yajima (2002) is crucial in view of determining the existence of a common value for δ_a and δ_b although this value remains unknown. Following Nielsen and Shimotsu (2007), we trivially estimate this common value, termed δ_*, by $\bar{\delta}_* = p^{-1}\sum_{a=1}^{p}\hat{\delta}_a$, $p = 2$ (see Table 3).[15] Then, we estimate $G(\delta_*)$ by substituting δ_* with $\bar{\delta}_*$. The bandwidth m_1 is introduced in estimating the matrix $G(\delta_*)$ to ensure that $\bar{\delta}_*$ converges to δ_* at a faster rate than $\hat{G}(\bar{\delta}_*)$ to $G(\bar{\delta}_*)$. We can employ both, the matrix $\hat{G}(\bar{\delta}_*)$ and the correlation matrix $\hat{P}(\bar{\delta}_*) = \hat{D}(\bar{\delta}_*)^{-1/2}\hat{G}(\bar{\delta}_*)\hat{D}(\bar{\delta}_*)^{-1/2}$ with $\hat{D}(\bar{\delta}_*) = \text{diag}\{\hat{G}_{11}(\bar{\delta}_*), \ldots, \hat{G}_{pp}(\bar{\delta}_*)\}$, $p = 2$, to estimate the rank. Denoting τ_i the i-th eigenvalue of $\hat{G}(\bar{\delta}_*)$ or $\hat{P}(\bar{\delta}_*)$,

[14] Given that the 2S-ELW is consistent for $\delta \in (-1/2, 2)$ and has a normal limit distribution $\sqrt{m}(\hat{\delta} - \delta) \xrightarrow{d} N(0, 1/4)$, it accommodates both the stationary and the non-stationary regions of the parameter space.

[15] We cannot perform a constraint estimation of the 2S-ELW because $G(\delta_a = \delta_b = \delta_*) = \frac{1}{m_1}\sum_{j=1}^{m_1} I_{\Delta(L;\delta_*,\delta_*)r}(\lambda_j)$ does not have full rank in presence of cointegration, with $\Delta(L;\delta_*,\delta_*)r = (\Delta^{\delta_*}r_{t,a}, \Delta^{\delta_*}r_{t,b})'$ and $\lambda_j = 2\pi jn^{-1}$ are the Fourier frequencies.

the rank estimate is defined as

$$\hat{r} = \arg \min_{u=0,\dots,p-1} L(u), \qquad L(u) = \upsilon(n)(p-u) - \sum_{a=1}^{p-u} \tau_a, \qquad p = 2 \tag{3}$$

Equation of $L(u)$ embed an additional tuning parameters, $\upsilon(n)$, for which the procedure is highly sensitive. In our application, we employ $\upsilon(n) = m_1^{-k}$ with $k = \{0.35, 0.25\}$. Simulations of Nielsen and Shimotsu (2007) reveal that for high values of k, the procedure is more likely to provide underestimate of $\hat{r}$ while for small values of k, the procedure is more likely to provide overestimate of $\hat{r}$.

Table 3: Empirical estimates of δ_* based on 2S-ELW estimates with $m = \lfloor n^{0.5} \rfloor$

$\bar{\delta}_*$	STI	PSEI	KLCI	JCI	HSI	NKY	SPX
SET	0,452	0,311	0,387	0,342	0,524	0,399	0,479
STI		0,390	0,466	0,421	0,603	0,478	0,559
PSEI			0,325	0,280	0,462	0,337	0,417
KLCI				0,357	0,539	0,413	0,494
JCI					0,494	0,368	0,449
HSI						0,550	0,631
NKY							0,505

2.7. *The regression-based approach*

The aforementioned rank analysis procedure does not provide information about the strength of the long-run relationship. Accordingly, the regression-based approach is particularly interesting to go further in the cointegration analysis. In view of anticipating the possible non-stationarity of the observed series (i.e. $\delta \geq 1/2$) we apply the exact local Whittle estimator of fractional cointegration (ELW-FC) developed by Shimotsu (2012). This estimator jointly estimates all the parameters of interest, β, γ and δ (henceforth denoted θ). It operates in two-steps to improve efficiency.

The first stage consists of applying a tapered[16] version of the local Whittle (LW) estimator of Robinson (2008) to estimate the cointegrated systems. Let θ^d regroups long memory parameters such as $\theta^d = (\gamma, \delta)'$. Then, the objective function of the tapered LW estimator is defined by,

$$R(\theta) = \log\det\hat{\Omega}(\theta) - 2(\gamma+\delta)\frac{q}{(1-\kappa)m}\sum_{j(q,\kappa)}^{m} \log\lambda_j, \tag{4}$$

$$\hat{\Omega}(\theta)\frac{q}{(1-\kappa)m} = \sum_{j(q,\kappa)}^{m} \mathrm{Re}\left[\Psi(\lambda_j;\theta^d)BI_r(\lambda_j)B'\Psi(\lambda_j;\theta^d)^*\right], \qquad B = \begin{pmatrix} 1 & -\beta \\ 0 & 1 \end{pmatrix} \tag{5}$$

[16]See Velasco (1999) for a discussion about tapered estimators.

where $\Psi(\lambda_j;\theta^d) = \operatorname{diag}\left(\lambda^{\gamma}, \lambda^{\delta} e^{-i(\pi-\lambda_j)(\delta-\gamma)/2}\right)$, $I_r(\lambda_j)$ is the tapered periodogram matrix of r_t, $\lambda_j = 2\pi j n^{-1}$ are the Fourier frequencies and $\sum_{j(q,\kappa)}^{m}$ is the sum taken over $j = q, 2q, \ldots, m$ for $j \leq \lfloor \kappa m \rfloor$ and q the order of the taper. Conversely to the original LW estimator, the phase parameter is not estimated but modeled as $(\delta-\gamma)\pi/2$. Shimotsu (2012) also introduces a trimming parameter, κ, to control the behavior of the objective function when $\delta - \gamma > 1/2$. In the context of our application this trimming parameter take the following values $\kappa = \{0.05, 0.04\}$.

The second stage consists of an application of the 2S-ELW of Shimotsu (2010) to obtain θ^* as $\theta^* = \arg\min_{\theta\in\Theta} R^*(\theta)$, given the concentrated objective function,

$$R^*(\theta) = \log\det\tilde{\Omega}^*(\theta) - 2(\gamma+\delta)\frac{1}{m}\sum_{j=1}^{m}\log\lambda_j, \tag{6}$$

$$\tilde{\Omega}^*(\theta) = \frac{1}{m}\sum_{j=1}^{m}\operatorname{Re}\left[I_{\Delta^{\theta^d}r}(\lambda_j;\beta)\right], \qquad I_{\Delta^{\theta^d}r}(\lambda_j;\beta) = \omega_{\Delta^{\theta^d}r}(\lambda_j;\beta)\bar{\omega}_{\Delta^{\theta^d}r}(\lambda_j;\beta) \tag{7}$$

$$\omega_{\Delta^{\theta^d}r}(\lambda_j;\beta) = \begin{pmatrix} \omega_{\Delta^{\gamma}(r_{t,a}-\beta r_{t,b})}(\lambda_j) \\ \omega_{\Delta^{\delta}r_{t,b}}(\lambda_j) \end{pmatrix} \tag{8}$$

with Θ the parameter space of θ^* and $\omega_r(\lambda_j)$ the discrete Fourier transform of r_t.

Denoting $\hat{\theta}$ the estimate of θ from aforementioned tapered LW estimator, the 2S-ELW-FC estimator of Shimotsu (2012) is defined as $\theta^* = \hat{\theta} - \left((\partial^2/\partial\theta\partial\theta')R^*(\hat{\theta})\right)^{-1}\left((\partial/\partial\theta)R^*(\hat{\theta})\right)$.[17] The author shows that $m^{1/2}\operatorname{diag}\{\lambda_m^{-v_0}, 1, 1\}(\theta^* - \theta_0) \xrightarrow{d} N(0, \Xi^{-1})$ as $n \to \infty$ when $v_0 \in (0, 1/2)$ and $m^{1/2}(\theta^{d*} - \theta_0^d) \xrightarrow{d} N(0, \Xi_{\theta^d}^{-1})$ while $(\beta^* - \beta_0) = O_p(n^{-v_0})$ as $n \to \infty$ when $v_0 \in (1/2, 3/2)$ with v_0 the true value of $v = (\delta - \gamma)$. Exploiting $\tilde{\Omega}^*(\theta)$, this procedure is also able to estimate the off-diagonal parameter, ρ, of the residuals covariance matrix (i.e. endogeneity parameter).

3. Cointegration analysis

Table 4 reports the test statistic $\hat{T}_0$ for the 2S-ELW estimates of the pairwise fractional integration orders (see Table 2). If the null hypothesis is accepted at conventional significance levels, the pairwise integration orders are equals. Since the 95% critical value of the χ_1^2 distribution is 3,84 we easily accept, in most cases, the null of equality of the integration order. At this stage, it is worth noting that the null hypothesis is always accepted at a 99% level of significance excepted for nine pairs including emerging with some developed markets. This suggest nonidentical, distinct or independent volatility process between the emerging and developed markets. Regarding equality of integration

[17] According to the author, an iterative procedure may result from estimation of θ^* without modifying the asymptotic distribution and may improve the finite sample properties.

orders among developed markets, the null hypothesis is always accepted with the only exception of Japan with Hong Kong, while the volatility processes of emerging markets always exhibit a common order of fractional integration. Accordingly, the fractional cointegration hypothesis can be investigated for 19 pairs of volatility series.[18]

Table 4: Test for the homogeneity of integration orders with $m = \lfloor n^{0.5} \rfloor$ and $h(n) = (\log n)^{-1}$

T_0	STI	PSEI	KLCI	JCI	HSI	NKY	SPX
SET	3,126	2,063	0,101	0,506	11,854	0,308	5,321
$\phi_\chi(T_0)$	(0,077)	(0,151)	(0,751)	(0,477)	(0,001)	(0,579)	(0,021)
STI		11,130	2,242	8,161	5,032	2,227	0,708
$\phi_\chi(T_0)$		(0,001)	(0,134)	(0,004)	(0,025)	(0,136)	(0,400)
PSEI			2,941	0,519	21,675	3,621	13,406
$\phi_\chi(T_0)$			(0,086)	(0,471)	(0,000)	(0,057)	(0,000)
KLCI				1,057	8,832	0,060	3,798
$\phi_\chi(T_0)$				(0,304)	(0,003)	(0,806)	(0,051)
JCI					19,249	1,687	10,048
$\phi_\chi(T_0)$					(0,000)	(0,194)	(0,002)
HSI						9,660	1,520
$\phi_\chi(T_0)$						(0,002)	(0,218)
NKY							4,613
$\phi_\chi(T_0)$							(0,032)

Notes: P-values are displayed in parentheses (.).

Following Nielsen and Shimotsu (2007), the rank estimates are conducted by using the correlation matrix $\hat{P}(\bar{\delta}_*)$. The results are presented in Table 5. In the bivariate case u takes the value 0 or 1 depending on the rank estimate. We adopt the regression-based approach to confirm the rank analysis and give more intuitive results about the strength of the long-term relationships. Table 6 reports the results of the ELW-FC estimates for $m = \lfloor n^{0.5} \rfloor$ and $\kappa = 0.05$.[19]

According to the rank analysis, the results indicate the presence of several cointegration relationships. Indeed, for the case with the lowest $\upsilon(n)$, i.e. $\upsilon(n) = m_1^{-0,25}$, we find eleven pairs for which the volatility processes are co-persistent. Again, we find a strong heterogeneity among the sample. For instance, the volatility of the emerging stock markets (i.e. PSEI, KLCI, SET, and JCI) appear to be well tied together while the share of commonality with their regional (STI, HSI and JPY) and global (SPX) counterparts is less evident. Conversely, HSI, STI are pairwise fractionally cointegrated both with each other and SPX, while NKY is pairwise fractionally cointegrated with only STI and SPX. As mentioned above, the procedure is sensitive to the tuning parameter $\upsilon(n)$, and co-persistence among emerging markets disappear when $\upsilon(n) = m_1^{-0,35}$. Overall, it follows that only developed stock markets, i.e. HSI, STI, NKY, and SPX, are pairwise fractionally cointegrated (except for the pair including HSI and NKY since their integration orders are not equals) and this finding is robust to the use of different tuning parameter values.

[18] We choose the regressor according to the market capitalization (see Table 1).

[19] Our results are not sensitive to the trimming parameter κ. However, we apply a penalty parameter to the coefficient $\hat{\beta}$ for the pairs HSI-SPX and KLCI-NKY because of convergence considerations of the concentrated objective function (see Shimotsu , 2012).

Table 5: Pairwise rank estimates based on $\hat{P}(\bar{\delta}_*)$

	SET/SPX		KLCI/SPX		STI/SPX		HSI/SPX		NKY/SPX	
$\upsilon(n)$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$
$L(0)$	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194
$L(1)$	-1,240	-1,117	-1,196	-1,074	-1,590	-1,467	-1,523	-1,400	-1,497	-1,374
$\hat{r}$	0	0	0	0	1	1	1	1	1	1
	PSEI/NKY		SET/NKY		JCI/NKY		KLCI/NKY		STI/NKY	
$\upsilon(n)$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$
$L(0)$	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194
$L(1)$	-1,237	-1,114	-1,215	-1,092	-1,335	-1,212	-1,224	-1,101	-1,538	-1,415
$\hat{r}$	0	0	0	0	0	1	0	0	1	1
	STI/HSI		SET/STI		KLCI/STI		PSEI/KLCI		SET/KLCI	
$\upsilon(n)$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$
$L(0)$	-1,440	-1,194	-1,440	-1,194	-(1,440)	-1,194	-1,440	-1,194	-1,440	-1,194
$L(1)$	-1,599	-1,476	-1,297	-1,174	-1,351	-1,228	-1,298	-1,175	-1,255	-1,132
$\hat{r}$	1	1	0	0	0	1	0	0	0	0
	JCI/KLCI		PSEI/JCI		SET/JCI		PSEI/SET			
$\upsilon(n)$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$	$m_1^{-0,35}$	$m_1^{-0,25}$		
$L(0)$	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194	-1,440	-1,194		
$L(1)$	-1,325	-1,202	-1,331	-1,208	-1,353	-1,230	-1,347	-1,224		
$\hat{r}$	0	1	0	1	0	1	0	1		

The estimates of β which are not significants at conventional levels imply the absence of long-run co-movement between the two markets. Consequently, KLCI is not fractionally cointegrated with NKY, STI, PSEI, SET, and JCI while, SET, PSEI and JCI are not pairwise fractionally cointegrated with each other. Taking as a whole, these results are consistent with the conclusions drawn on the basis of the regression analysis., except for the pair including STI and NKY for which the estimate of β is insignificant. In such a case, we must be careful when interpreting the estimation results.

Interestingly, the estimates of β are larger among developed markets in most cases, suggesting again a strong correlation among their volatility processes. For instance, correlations between SPX and STI, HSI and NKY, are equal to 0.769, 0.641 and 0.723, respectively. We find also a large $\hat{\beta}$ for STI-HSI (0.91), SET-JCI(1.309) and SET-KLCI(1.160). Conversely, the long-term correlations among the emerging and developed markets are less than one-half in most cases.

Another necessary condition to establish a fractional cointegration relationship between two series is $\hat{\gamma} < \hat{\delta}$. In most cases, the cointegrating residuals have substantially smaller memory parameters estimates than $\hat{\delta}$, suggesting fractional cointegration between these pairwise volatility series. In addition, the gap between the estimates of $\hat{\delta}$ and $\hat{\gamma}$, provides informations about the persistence of deviations from the long-run equilibrium. The higher the gap between δ and γ, the greater the strength of the cointegrating relation. The values $\hat{\delta} - \hat{\gamma}$ are particularly high for the cointegrated

Table 6: ELW-FC estimates for $m = \lfloor n^{0.5} \rfloor$ and $\kappa = 0.05$

	SET/SPX		KLCI/SPX		STI/SPX		HSI/SPX		NKY/SPX	
$\hat{\beta}$	0,429	(0,090)	0,341	(0,092)	0,769	(0,128)	0,641	(0,107)	0,723	(0,105)
$\hat{\gamma}$	0,295	(0,066)	0,386	(0,065)	0,426	(0,066)	0,501	(0,065)	0,349	(0,066)
$\hat{\delta}$	0,602	(0,066)	0,606	(0,065)	0,588	(0,066)	0,700	(0,065)	0,584	(0,066)
$\hat{\rho}$	-0,150		-0,254		-0,187		-0,282		-0,158	
	PSEI/NKY		**SET/NKY**		**JCI/NKY**		**KLCI/NKY**		**STI/NKY**	
$\hat{\beta}$	0,160	(0,068)	0,575	(0,228)	0,431	(0,109)	0,370	(0,446)	0,794	(0,741)
$\hat{\gamma}$	0,131	(0,066)	0,256	(0,065)	0,126	(0,066)	0,381	(0,066)	0,465	(0,066)
$\hat{\delta}$	0,427	(0,066)	0,422	(0,065)	0,430	(0,066)	0,439	(0,066)	0,425	(0,066)
$\hat{\rho}$	0,183		-0,214		0,132		-0,171		-0,087	
	STI/HSI		**SET/STI**		**KLCI/STI**		**PSEI/KLCI**		**SET/KLCI**	
$\hat{\beta}$	0,910	(0,035)	0,605	(0,120)	0,301	(0,188)	0,428	(0,112)	1,160	(0,316)
$\hat{\gamma}$	0,244	(0,066)	0,265	(0,066)	0,401	(0,066)	0,108	(0,066)	0,210	(0,065)
$\hat{\delta}$	0,678	(0,066)	0,537	(0,066)	0,523	(0,066)	0,401	(0,066)	0,402	(0,065)
$\hat{\rho}$	0,101		-0,120		0,194		0,036		-0,290	
	JCI/KLCI		**PSEI/JCI**		**SET/JCI**		**PSEI/SET**			
$\hat{\beta}$	0,616	(0,387)	0,277	(0,187)	1,309	(0,451)	0,251	(0,110)		
$\hat{\gamma}$	0,237	(0,065)	0,194	(0,066)	0,213	(0,057)	0,170	(0,065)		
$\hat{\delta}$	0,403	(0,065)	0,310	(0,066)	0,305	(0,057)	0,371	(0,065)		
$\hat{\rho}$	0,232		0,154		-0,719		0,262			

Notes: Standard deviations are displayed in parentheses (.).

pair including Hong Kong with Singapore (0.435). We also observed some interesting relationships between emerging and developed markets, such as PSEI-NKY (0.296), JCI-NKY (0.304), SET-SPX(0.308). Again, we need to be careful about the relevancy of these findings since this procedure is sensitive to the bandwidth selection and other tunning parameters.[20] Nonetheless, these last findings seem to confirm that the developped markets, especially Hong Kong and Singapore, are closely linked in the long run with both each other and the US stock market.

4. Concluding remarks

In this study, we examine the integration of stock markets in several emerging and developed Asian markets. Conversely to most of the existing studies that investigate the short-term correlation, we focus on long-term cross-border correlation of integrated volatilities. More precisely, we investigate the persistent and the co-persistence nature of volatility processes by means of fractional cointegration techniques. We implement a robust methodology that relies on both, the rank estimate and the regression-based analysis. Our findings confirm that developed stock markets in Asia are globally integrated with the world stock market of the US, consistently with the view expressed by Dao

[20] For robustness, we also study a parametric form of the model in Eq. (1) using the quasi-maximum likelihood (QML) estimator of de Truchis (2013). According to this investigation, short run dynamics of the cointegrating errors are fairly complex and encourage us to consider small bandwidths. We find that results are not so different as regards the relation of interest, although the QML estimator seems to widely underestimate β.

and Wolters (2008) who concluded that volatilities in Singapore, Hong Kong, Japan an US stock markets are in essence co-persistent. Accordingly, volatilities in the US and developed markets in Asia respond in a similar way to shocks, implying greater co-movements in the long run among their volatility process. This also implies that effective diversification of portfolios among these markets cannot be achieved in the long run. It is worth noting that empirical results concerning the Japanese stock market are mixed, since only the pair including the SPX is robust to the two fractional cointegration methods. This means that the Japanese stock market is integrated with the world stock market of the US but not with those of Hong Kong and Singapore. The fact that Japan holds a sizable share of its total foreign assets in the form of US assets (32.3 % in 2009) and invests very little in Asia (2.4% in 2009) may provide evidence of such an integration with the US stock market (see Park and lee , 2011 for details on the pattern of cross-border financial asset holdings in Asia).

Conversely, there is only little evidence of co-persistence among the emerging markets (i.e. PSEI, JCI, KLCI and SET), which appear to be segmented at both regional and global levels over the 2000-2012 period. This suggests that these markets do not share in the long run commonalities in the market fundamentals underlying their volatility processes. These results are consistent with Harvey (1995) and Beckaert and Harvey (1995), who argue that emerging markets are more likely to be influenced by local events. Yu et al. (2010) explain the divergence in integration by the lack of harmonization of standards in capital markets and the absence of links between jurisdictions across the whole spectrum of financial infrastructure. Therefore, the emerging markets in Asia need to address these issues in the planning of a coordinated strategy for promoting financial integration within the region, along with their political support toward greater financial cooperation. This would help the region to improve resilience against country-specific shocks via the cross-ownership of equity capital. On the other hand, from the point of view of individual investors who seek to diversify in these emerging markets, the little evidence of co-persistence indicates that, in the long run, the potential benefits of international portfolio diversification remain effective.

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