On measuring synchronization of bulls and bears: the case of East Asia

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Abstract

The paper implements estimation and testing procedures for comovements of stock market "cycles" or "phases" in Asia. We extend the Harding and Pagan (2006) test for Strong Multivariate Nonsynchronization (SMNS) between business cycles to a test that allows for an imperfect degree of multivariate synchronization between stock market cycles. Moreover, we also propose a test for endogenously determining structural change in the bivariate and multivariate synchronization indices. Upon applying the technique to five Asian stock markets we found a significant increase in the cross country comovements of Asian bullish and bearish periods in 1997. A power study of the stability test suggests that the detected increase in comovement is more of a sudden nature (i.e. contagion or "Asian Flu") instead of gradual (i.e. financial integration). It is furthermore argued that stock market cycles and their propensity toward (increased) synchronization contain useful information for both investors, policy makers and financial regulators.

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1 Introduction

In the past couple of years, financial economists have extensively documented so-called "empirical stylized facts" of stock market returns such as clusters of volatility and heavy tails, see e.g. Embrechts et al. (1997). That stock prices typically exhibit periods of persistent rises or falls, i.e., so-called "bulls" and "bears", has been recognized by the financial practitioners for a long time but has attracted much less attention from the academic community.[1] Accordingly, the potential for stock markets to be simultaneously bullish or bearish across geographical borders has also stayed underexposed. The main objective of the paper will therefore consist in providing a framework for measuring synchronization between stock market cycles and how it evolved over time.[2]

Measuring stock market cycles and their cross-border synchronization is of potential interest for both investors and policy makers. First, it is common sense that investors rebalance their portfolios by purchasing "cheap" stocks during bearish periods and selling "expensive" stocks when stock markets are bullish. The question arises, however, how to optimally time this portfolio rebalancing. Technical analysts typically time their buying and selling decisions by means of graphical analysis. A more thorough statistical analysis of bulls and bears could help investors to further improve the timing of their investment decisions. The above discussion suggests that the duration of a stock cycle constitutes the natural time horizon for a "single-cycle" or "short-term" investor (or, alternatively, constitutes the natural time horizon

[1]Traditionally, there are two perspectives on these observed persistent rises or falls in stock prices. First, they may be induced by irrational "animal spirit" (or sentiment that is unrelated to any rational expectations of future fundamental values), see e.g. Summers (1986), Shiller (2000) or Anderson et al. (2003). These papers argue that prices can sometimes display seemingly persistent deviations from their long-run equilibrium values. Another view states that, although market sentiment can drive away prices quite substantially from fundamentals in the short run, proportional differences between market prices and fundamentals are kept within bounds and stocks markets exhibit a long-run relation between prices and fundamentals indeed, see e.g. De Long (1992), Siegel (1998) or Coakley and Fuertes (2006). This paper does not fit in either of these two strands of literature as we do not aim to disentangle the causes of stock market bulls and bears.

[2]Nonsurprisingly, most studies on cycles and cyclical comovements focus on real economic time series and the business cycle, see e.g. Harding and Pagan (2004) for a survey. In contrast, few empirical studies identified and investigated univariate features of stock market cycles, see e.g. Edwards et al. (2003), Gomez Biscarri and Perez de Gracia (2002, 2003), Pagan and Sossounov (2003) or Lunde and Timmerman (2004). An even smaller set of papers looked into whether stock market cycles comove, see e.g. Gomez Biscarri and Perez de Gracia (2002, 2003), Edwards et al. (2003) and Harding and Pagan (2006). Booms and slumps in commodity prices have been considered by Cashin et al. (2002).

for portfolio rebalancing in case of a "multi-cycle" or "long-term" investor). Thus, in order to assess the potential for risk diversification across stock market cycles, it seems natural to consider correlations over the duration of a typical stock market cycle and not on, say, a daily or monthly basis. The latter correlation measures might offer a misleading view on the potential for risk diversification if investors base their rebalancing decisions on stock market cycles.

Also, persistent swings in stock market prices and the potentially destabilizing effects on the real economy raises the issue if and how monetary authorities should respond. Indeed, bullish stock markets can induce large amounts of loan collateral - especially in less developed banking systems with poor regulatory frameworks - which then increases demand and goods price inflation. Moreover, when the stock market bulls turn into bears, this can result in widespread liquidity problems and a "credit crunch" in the financial system. Thus, monitoring the impact of stock market swings is also of potential interest to regulatory bodies caring about systemic risk and overall financial stability. Finally, if stock cycles have become more synchronized over time, the potential for financial system instability to spill over to other countries has also increased which seems to suggest that a coordinated effort of policymakers and regulatory bodies might be necessary.

The paper makes several contributions to the stock market bulls and bears cum synchronization literature.[3] More specifically, we extend the Generalized Method of Moments (GMM) approach to measuring business cycle synchronization due to Harding and Pagan (2006) toward estimating and testing for (bivariate, multivariate) cyclical stock market synchronization. First, we allow for a value of the "common" synchronization index between -1 and 1 whereas Harding and Pagan only consider tests for the benchmark cases of

[3]Preceding literature on stock market synchronization is vast and difficult to summarize. Early research on stock market linkages mainly documented cross border return correlations (see e.g. Jaffe and Westerfield (1985); Roll (1988)). This correlation analysis was refined later on, either by implementing multivariate stochastic volatility (SV) models or cointegrated Vector Auto Regressions (VAR). Representative articles of the former "school" include King and Wadhwani (1990); Hamao et al. (1990); Malliaris and Urrutia (1992); Lin et al. (1994); Susmel and Engle (1994). These ARCH-type models were used, inter alia, to investigate the direction of international spillovers as well as to identify differences in market comovements in periods of market turbulence and market quiescence. Baillie and Bollerslev (1992), however, argued that the modelling of returns can result in a loss of information on possible common trends when prices are cointegrated. Researchers have therefore also turned attention to VAR frameworks that take cointegration and error correction into account. Representative articles of the cointegrated VAR literature are Click and Plummer (2005); Chen et al. (2002); Ghosh et al. (1999); Kasa (1992); Jeon and Chiang (1991).

complete perfect synchronization or nonsynchronization. Second, the estimation and testing procedure for multivariate synchronization is complemented with an endogenous stability test for detecting time variation in cyclical stock market synchronization. Third, our stability testing procedure can be seen as extending a scant preceding literature on structural change in cyclical stock market synchronization (see e.g. Gomez Biscarri and Perez de Gracia (2002) and Edwards et al. (2003)). The latter papers tried to investigate the stability of bivariate concordance indices by means of rolling regressions.

Emerging markets are the more obvious candidates for detecting changes in cyclical stock market synchronization due to the rapid transformation of their financial systems and the recurrent financial crises, see e.g. Bekaert and Harvey (2001). We therefore select a set of Asian stock markets in our empirical application. Furthermore, we show via Monte Carlo simulation that the stability test seems to be able to detect contagion-like processes but not gradual changes. In that sense, our paper complements a recent literature on Asian contagion identification, see e.g. Forbes and Rigobon (2002), Bond et al. (2006) or Dungey et Martin (2003, 2004, 2006).

The remaining sections are organized as follows. Section 2 discusses the statistical estimation and testing methodology that will be implemented. Section 3 evaluates the small sample properties of the stability test (size, power) and proposes a bootstrap method for determining the size-corrected small sample critical values. Empirical estimation and testing results are reported in section 4. Concluding remarks are contained in section 5.

2 Methodology

The concept of imperfect multivariate equity market synchronization is introduced in section (2.1). Next we propose a GMM-based testing procedure for detecting structural change in the multivariate synchronization measure (2.2).

2.1 Strong multivariate synchronization of degree ρ_0

Harding and Pagan (2006) introduced the concept of synchronization for measuring business cycle comovements. We shorty describe their GMM framework together with the extensions of Candelon et al. (2006).

Prior to calculating cyclical correlations we need to identify what stock market "bulls" or "bears" are. The financial press nowadays usually focuses on increases (declines) of the market being greater (less) than either 20% or 25%, see Pagan and Sossounov (2003). As for the academic literature,

there is no consensus on what bulls and bears actually mean. One definition describes bull or bear markets as "periods of generally increasing/decreasing market prices", see Chauvet and Potter (2000, p. 90, fn.6). The former definition, by focusing on extreme movements, would be analogous to "booms" and "busts" in the real economy whereas the latter definition seems closer to reflecting busiess cycle contractions and expansions. We use the latter definition of bulls and bears that focuses on how stock prices evolve between local peaks and troughs. This approach is in line with the business cycle literature going back to Burns and Mitchell (1946). The definition essentially implies that a bullish stock market turned bearish if prices have declined for a substantial period since their previous (local) peak. Such a definition does not exclude sequences of price falls (rises) during a bull (bear) phase, but there are restrictions on the extent to which these sequences of price reversals can occur and yet still be considered part of any given bull or bear phase.

Let p_{it} denote the log stock price for country i at time t ($i = 1, \cdots, n; t = 1, \cdots, T$). Bull and bear periods are determined using the marginal transform (or "filter") $\varphi(.)$ such that $\varphi(p_{it}) = S_{it}$ $(\forall i)$ where S_{it} is 0 or 1 in case of bear or bull period, respectively. There are two main methodological strands in the literature to select the filter $\varphi(.)$. One approach, proposed by Hamilton (1989) imposes a Markov-Switching model on $\varphi(.)$ that allows for two different regimes, one for booms and one for busts.[4] We prefer a nonparametric approach which might be motivated by the complex temporal behavior of financial time series (clusters of volatility, long memory etc.) and the resulting risk of model misspecification. The key feature of nonparametric filters or dating algorithms is the location of turning points (peaks and troughs) that correspond to local maxima and minima of the series. Loosely speaking, a peak/trough in the (log) stock price series p_{it} occurs when p_{it} reaches a local maximum (minimum) in a window of width of 6 months.[5] For a peak to occur at t, this implies:

$$\begin{aligned} p_{i,t-6} &< \cdots < p_{i,t-1} < p_{i,t} \\ &\text{and} \\ p_{i,t} &> p_{i,t+1} > \cdots > p_{i,t+6} \end{aligned}$$

[4]Examples of this dating approach include e.g. Goodwin (1993), Diebold and Rudebusch (1996), Kim and Nelson (1999) for business cycles; as for stock market cycles important references include e.g. Hamilton and Lin (1996), Ramchand and Susmel (1998) and Maheu and McCurdy (2000).

[5]Robustness checks to different window widths are not included for sake of space considerations. Turning point locations only change marginally. Results are available upon request.

Likewise there will be a trough at t if

$$\begin{aligned} p_{i,t-6} &> \cdots > p_{i,t-1} > p_{i,t} \\ &\text{and} \\ p_{i,t} &< p_{i,t+1} < \cdots < p_{i,t+6} \end{aligned}$$

The above dating algorithm constitutes the core of a more complicated method proposed by Bry and Boschan (1971) in order to date business cycle phases at the quarterly frequency. This approach has since also been used to determine stock market cycles, see e.g. Gomez Biscarri and Perez de Gracia (2002), Kaminsky and Schmukler (2003) or Pagan and Sossounov (2003). Once turning points are determined, bull and bear periods can be identified as periods between peaks (troughs) and troughs (peaks), respectively. [6]

Harding and Pagan (2006) proposed GMM-based multivariate procedures for testing the null hypothesis that business cycles are either perfectly synchronized or not synchronized at all. Candelon et al. (2006) argued that these two borderline null hypotheses might be a bit unrealistic and propose a more general framework to test for strong (but imperfect) multivariate synchronization of degree ρ_0 ($-1 < \rho_0 < 1$) or SMS(ρ_0) in shorthand notation.[7] Their procedure starts from the following $n\left(n+1\right)/2$ moment conditions under the null hypothesis SMS(ρ_0):

$$E\left[h_t(\theta_0, S_t)\right] = 0 \tag{1}$$

with

$$h_t\left(\theta_0, S_t\right) = \begin{bmatrix} S_{1t} - \mu_1 \\ \vdots \\ S_{nt} - \mu_n \\ \frac{(S_{1t}-\mu_1)'(S_{2t}-\mu_2)}{\sqrt{\mu_1(1-\mu_1)\mu_2(1-\mu_2)}} - \rho_0 \\ \vdots \\ \frac{\left(S_{(n-1)t}-\mu_{n-1}\right)'(S_{nt}-\mu_n)}{\sqrt{\mu_{n-1}(1-\mu_{n-1})\mu_n(1-\mu_n)}} - \rho_0 \end{bmatrix} \tag{2}$$

[6] Throughout the rest of the paper we allow for two regimes but generalization of the framework to more than two dimensions is straightforward.

[7] The borderline case of perfect multivariate synchronization ($\rho_0 = \pm 1$) is excluded from the analysis because it is unlikely to be observed and thus not very interesting for our empirical analysis. The asymptotic distribution in this limiting case turns out to be a weighted average of χ^2 distributions where the weights have to be determined by simulation, see Gourieroux et al. (1982).

and with $\theta_0' = [\mu_1, ..., \mu_n, \rho_0, ..., \rho_0]$ the restricted vector under the SMS(ρ_0) case. The expectations operator in (1) is defined over the time dimension. The 1st subset of n moment conditions in (1) defines the population means of the cycle dummies and reflect the likelihoods of the stock markets to be in the bullish phase; whereas the remaining $n\,(n-1)\,/2$ moment conditions express equality of all cyclical (Pearson-type) correlations to some common value ρ_0.If the above moment conditions hold, stock markets, albeit imperfectly synchronized, do exhibit a "common" or "homogeneous" synchronization index ρ_0.

Candelon et al. propose to test SMS(ρ_0) via Hansen's (1982) Wald test statistic:

$$W\left(\rho_0\right) = Tg(\theta_0, [S]_{t=1}^{T})'\hat{V}^{-1}g(\theta_0, [S]_{t=1}^{T}), \tag{3}$$

which converges to an asymptotic $\chi^2_{n(n-1)/2}$ distribution under the null hypothesis $\theta = \theta_0$, see e.g. Harding and Pagan (2006, p. 70). The covariance matrix $\hat{V}$ is a heteroskedastic and autocorrelation consistent (HAC) estimator of the variance-covariance matrix of $\sqrt{T}g(\theta_0, [S]_{t=1}^{T})$, see e.g. Newey and West (1994). The statistic is defined as a quadratic form in the penalty vector $g(\theta_0, [S]_{t=1}^{T}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\theta_0, S_t)$ which reflects the average deviation from the moment conditions. The stronger the deviations from the moment conditions the more likely a rejection of SMS(ρ_0) becomes.

Notice that the implementation of the Wald test (3) still hinges upon an (unknown) value for ρ_0. Candelon et al. (2006) propose a two-step estimation procedure: first, they determine the closed interval $[\rho_-, \rho_+]$ for which $SMS\left(\rho_0\right)$ cannot be rejected at a prespecified nominal size. Next, a natural estimator for ρ_0 follows by minimizing the test statistic in (3) over $[\rho_-, \rho_+]$:

$$\hat{\rho}_0 = Argmin_{\rho\in[\rho_-,\rho_+]}\left\{Tg(\theta_0, [S]_{t=1}^{T})'\hat{V}^{-1}g(\theta_0, [S]_{t=1}^{T})\right\} \tag{4}$$

In the next subsection we develop a framework to test for structural change in $\hat{\rho}_0$.

2.2 Structural breaks in multivariate synchronization

To the best of our knowledge, hardly no studies on co-cyclicality in time series considered yet the possibility of time variation in co-cyclicality.[8] This

[8]A few studies look at temporal stability of so-called "concordance" indices, see e.g. Edwards et al. (2003), or Gomez-Biscarri and Perez de Gracia (2002, 2003). However, the synchronization measure has several advantages over the concordance index. For a more in-depth discussion of the pitfalls of concordance indices, see e.g. Harding and Pagan (2006, p. 65).

may be partly due to the relative complexity of performing stability tests within a GMM framework. The full sample framework of Harding and Pagan (2006) makes the simplifying assumption that the cross sectional dependence structure of raw stock returns $(\Delta p_{1t}, \cdots, \Delta p_{it}, \cdots, \Delta p_{nt})$ and corresponding cycle dummies $(S_{1t}, \cdots, S_{it}, \cdots, S_{nt})$ remains stationary over the entire sample period. However, assuming stationarity seems problematic, especially for emerging markets that have been recently characterized by financial liberalization experiments (e.g. gradual abolishment of capital controls), recurrent changes in domestic supervisory rules, exchange rate regimes and severe financial crises, see e.g. Bekaert and Harvey (2001) for details on the reform processes in emerging countries.

To start the breakpoint analysis, we concentrate on the simplifying case of a known breakpoint at time $b = T_1/T$, i.e., a priori selected by the researcher. This implies that the full sample moment conditions in (1)-(2) become

$$\begin{cases} ES_{it} = \mu_i & i = 1, ..., n \\ E[\frac{(S_{it}-\mu_i)'(S_{jt}-\mu_j)}{\sqrt{\mu_i(1-\mu_i)\mu_j(1-\mu_j)}} - \rho_1^{ij}] = 0 & i = 1, ..., n, j \neq i, t = 1, ..., T_1 \\ E[\frac{(S_{it}-\mu_i)'(S_{jt}-\mu_j)}{\sqrt{\mu_i(1-\mu_i)\mu_j(1-\mu_j)}} - \rho_2^{ij}] = 0 & i = 1, ..., n, j \neq i, t = T_1 + 1, ..., T. \end{cases} \tag{5}$$

The latter set of moment conditions further differs from (1)-(2) in that (5) allows for correlation differences across stock market pairs ij.[9] This allows us to perform a restricted and an unrestricted version of the stability test. The null hypothesis of temporal stability in bivariate synchronization corresponds to the case where $\rho_1^{ij} = \rho_2^{ij}$ $(i = 1, \cdots, n; j \neq i)$. We call this null hypothesis the "weak" or "unrestricted" stability hypothesis as it does not require cross sectional equality of the bivariate synchronization index in each subsample (the existence of a multivariate synchronization index). On the other hand, the "strong" or "restricted" stability hypothesis $\rho_1 = \rho_2$ considers structural change in the multivariate synchronization index; this version of the test presupposes the cross sectional equality of bivariate correlations in each of the two subsamples ("homogeneous" bivariate synchronization). In order to disentangle changes in multivariate synchronization from time varying deviations in homogeneity, we will test the unrestricted version of the stability hypothesis in combination with subsample tests for multivariate synchronization (see previous section for a discussion of the latter test). If

[9] More specifically, $\rho_1^{ij}(\rho_2^{ij})$ stand for the bivariate Pearson correlation of the binary pair (S_{it}, S_{jt}) in the pre- (post-) break period.

homogeneity holds in the subsamples defined by the break, both the weak and strong stability test should render the same break estimates.

To facilitate the presentation of the stability test, it is worthwhile to introduce some additional notation. Let $\widehat{\theta}_k'(b) = [\widehat{\mu}_{k1}, ..., \widehat{\mu}_{kn}, \widehat{\rho}_k^{12}, ..., \widehat{\rho}_k^{n(n-1)}]$ be the (unrestricted) GMM estimator of θ' based on subsamples $k = 1, 2$ with $b = T_1/T$. The natural statistic for testing the unrestricted or restricted stability hypothesis is the Wald statistic proposed by Andrews and Fair (1988):

$$S_T(b) = T[\widehat{\theta}_1 - \widehat{\theta}_2]'\widehat{V}_S(b)^{-1}[\widehat{\theta}_1 - \widehat{\theta}_2],$$

where

$$\widehat{V}_S(b) = (1/b)[\widehat{F}_1(b)'\widehat{S}_1^{-1}(b)\,\widehat{F}_1(b)]^{-1} + (1/(1-b))[\widehat{F}_2(b)'\widehat{S}_2^{-1}(b)\,\widehat{F}_2(b)]^{-1},$$

and

$$\widehat{F}_1(b) = [T_1]^{-1}\sum_{t=1}^{T_1}\frac{\partial h_t(\widehat{\theta}_1(b), S_t)}{\partial\theta'}, \quad \widehat{F}_2(b) = [T-T_1]^{-1}\sum_{t=T_1+1}^{T}\frac{\partial h_t(\widehat{\theta}_2(b), S_t)}{\partial\theta'}$$

As in the previous section the deviations from the (subsample) moment conditions in (5) are defined by $g(\widehat{\theta}_1(b), \{S_t\}_{t=1}^{T_1}) = \frac{1}{T_1}\sum_{t=1}^{T_1} h_t(\widehat{\theta}_1, S_t)$ and $g(\widehat{\theta}_2(b), \{S_t\}_{t=T_1+1}^{T}) = \frac{1}{T-T_1}\sum_{t=T_1+1}^{T} h_t(\widehat{\theta}_2, S_t)$. Andrews and Fair (1988) showed that $S_T(b)$ converges to a $\chi^2_{n(n-1)/2}$ distribution.

We are now ready to consider the design of optimal tests for parameter variation at some unknown breakpoint. In line with Quandt's (1960) pioneering work on endogenous breakpoint determination in linear time series models, $S_T(b)$ can be calculated to produce a sequence of statistics indexed by b. This sequence can be used to construct a single statistic for testing the null hypothesis. Andrews (1993) suggests to select b such as to maximize $S_T(b)$:

$$Q_A(b^*) = \sup_{b\in B}\left\{T[\widehat{\theta}_1 - \widehat{\theta}_2]'\widehat{V}_S(b)^{-1}[\widehat{\theta}_1 - \widehat{\theta}_2]\right\}. \tag{6}$$

At the candidate break date b^* the constancy hypothesis is most likely to be violated.[10] Asymptotic critical values for Q_A are provided in the same paper.

Based on Quandt's basic idea, Andrews and Ploberger (1994) proposed two tests (the simple average and exponential tests) that complement Q_A.

[10] In accordance with Andrews (1993), the interval B is chosen equal to the closed interval $[0.15T; 0.85T]$ where T represents the total sample size.

However, upon comparing their performance, Hall (2005, p.183-184) concluded that "no one test dominates the others". We therefore limit our analysis to the Supremum functional. Before putting this stability test at work in an empirical application, we estabblish the small sample properties of the test which will reveal that blindly using asymptotic critical values from Andrews (1993) can be problematic when the dimension of the test (large number of markets or countries) grows large.

3 Monte-Carlo Experiments

Previous papers (in particular Christiano and Den Haan, 1996) argued that existing asymptotic theory for GMM estimators may break down in small samples. This problem might be more acute when the number of countries (cross sectional dimension) grows large relative to the length of the economic time series. For example, Candelon et al. (2006) have shown that the asymptotic version of the test for multivariate cycle synchronization of degree ρ_0 ($SMS(\rho_0)$) in eq. (**??**) is biased towards rejection for simulated processes that are representative for the business cycle literature. They therefore propose to bootstrap the small sample distribution of the test. In this section we perform a similar simulation study of size and power for the stability test (6) and for a number of data generating processes representative for financial data.

It is well known that unit root processes for the stock price are able to generate persistent rises or falls in simulated prices, see e.g. Pagan and Sossounov (2003). The unit root process $p_{it} = p_{it-1} + u_{it}$ will therefore act as a benchmark model.[11] The Monte Carlo investigation basically looks at the impact on the stability test's size and power of changing the distributional assumptions for the return $\Delta p_{it} = u_{it}$. First, returns Δp_{it} are drawn from a standard normal df.[12] However, the normal df does not capture the fat tail feature of financial asset returns, see e.g. Mandelbrot (1963) or Embrechts et al. (1997). We therefore also allow for student-t distributed innovations in the unit root process.[13] Finally, and in order to capture the clusters of

[11] For sake of simplicity we assume a zero drift term. However, our simulation results do hardly change in the presence of nonzero drift. Simulation results with nonzero drift were omitted for sake of space consideration but are available upon request.

[12] This special case for p_{it} is also called an independent and identically distributed Gaussian Random walk.

[13] The degrees of freedom parameter α equals the so-called tail index. In general, the tail index of a heavy tailed distribution reflects the number of bounded distributional moments that exist. Smaller values of the tail index imply relatively more probability mass in the tails as compared to return series with high values for α. Empirical studies typically find

volatility feature of financial returns (see e.g. Bollerslev (1986)), we used Bollerslev's Constant Conditional Correlation (CCC) model as simulation vehicle for the price innovations u_{it}. The mean equation, variance and covariance boil down to:

$$\begin{aligned} \Delta p_{i,t} &= u_{i,t} = \sqrt{h_{ii,t}}\epsilon_{i,t} \\ h_{ii,t} &= 0.01 + 0.2u_{i,t-1}^2 + 0.79h_{ii,t-1}, \end{aligned}$$

and

$$h_{ij,t} = 0.5\sqrt{h_{ii,t}h_{jj,t}}$$

The parameters driving the conditional volatilities are chosen such that the unconditional variance is equal to 1 (the same unconditional variance as with the normal and student-t innovations). The standardized residuals $\epsilon_{i,t}$ wil either be standard normally distributed or student-t distributed.[14]A well known drawback of the classic raw return correlation constitutes its sensitivity to increases in subsample volatility, see e.g. Forbes and Rigobon (2002). As a result, they argue that correlations should first be corrected for this volatility bias before one can interpret rises in correlation as providing evidence for either financial contagion or changes in interdependence. The CCC model framework enables us to investigate whether the same bias problem arises for the synchronization index.

Once we generated the data, we apply the Bry-Boschan dating algorithm to determine the dummy pairs $(S_{i,t}, S_{j,t})$. Without loss of generality we limit ourselves to considering the size of the stability test under the null hypothesis of strong multivariate non-synchronization ($SMNS$) (i.e. $E(u_{i,t}u_{j,t}) = 0$ and $E(\epsilon_{i,t}\epsilon_{j,t}) = 0$ in the described simulation procedures).[15]

Table 1 contains the small sample size of the stability test in eq. (6) and for different values of n (the number of countries). The nominal size is set to 5%. We report the small sample size that corresponds with the asymptotic critical values ("noncorrected") and with the bootstrapped critical values ("bootstrapped"). The sample size T is set at 250 which roughly

values for the tail index around 3 and this irrespective of the considered asset class. For the normal df, all moments exist and thus $\alpha = \infty$.

[14]It has been shown that the unconditional df of a GARCH(1,1) process exhibits heavy tails even if the standardized residuals $\epsilon_{i,t}$ are normally distributed, see e.g. Embrechts et al. (1997) or Mikosch and Starica (1998). Imposing a heavy tail on the residuals $\epsilon_{i,t}$ increases the probability mass in the tails of the unconditional df even further.

[15]Fairly similar size distortions arise when simulating under the null hypothesis SMS(ρ_0), with $\rho_0 \neq 0$. The latter simulations are therefore omitted for sake of space considerations but are available upon request.

corresponds with the sample size in the empirical application. The upper panel reports simulation outcomes for normally distributed and student-t distributed returns whereas the lower panel is generated by simulating from the CCC model. The table further distinguishes between unrestricted and restricted stability tests. In the former case one leaves bivariate correlations unrestricted in the pre-break and post-break vectors θ_1 and θ_2 whereas the restricted stability test is only implemented for those simulation replications that are consistent with a common synchronization index over the full sample, i.e., when the null hypothesis SMS(ρ_0) is not rejected. Finally, the bootstrap is performed on the binary series and not on the original data. Moreover, and in order to take into account the temporal persistence in the cycle variables, we bootstrap in blocks of length 25.[16] Further details on the block bootstrap procedure are provided in appendix.

First and foremost, the table shows that small sample size distortions using the asymptotic critical values ("noncorrected" rows) are present and growing with the number of countries. If one tests for structural stability in θ for 5 countries simultaneously, the asymptotic GMM testing procedure becomes completely untrustworthy because one would nearly always reject the (true) null hypothesis of absence of breaks in multivariate synchronization. The size distortions are somewhat less severe in the restricted case but still too big to justify the use of asymptotic critical values. In order to remedy the size distortion we perform a block bootstrap along the lines of Candelon et al. (2006). The bootstrapped critical values exceed their asymptotic counterparts and bring down the small sample size in the neighborhood of 5% in the majority of the cases.

The table further reveals that the magnitude of the asymptotic size distortions as well as the performance of the bootstrap algorithm does not seem to be influenced by the choice of stochastic process in simulation. More specifically this implies, inter alia, that volatility clusters (Panel B) do not induce extra overrejections of the stability hypothesis as compared to models without conditional volatility changes (panel A). Otherwise stated, the synchronization index and accompanying stability test do not need Forbes-

[16] To our knowledge, there is no rule-of-thumb for choosing the optimal block length for a bootstrap in a GMM context. Hall *et al.* (1995) established optimal block lengths for some stochastic processes but none of them is representative of the GMM framework we are using. Thus, it should not surprise we found that block bootstraps with block lengths conform the Hall et al. criteria only partially eliminate the size distortion. As an alternative strategy, we compared the performance of the block bootstrap for a grid of block lengths and found by trial and error that block sizes of 25 more or less eliminate the size distortion. Simulations are not included for sake of space considerations but are available upon request.

Rigobon type corrections for clusters of high volatility.[17]

[Insert Table 1]

Using size-corrected critical values obtained via the bootstrap, we can now also evaluate the size-corrected power of the stability test. Our power study assumes different adjustment paths and different adjustment speeds for moving from the pre-break synchronization index ρ_1 to its post-break counterpart ρ_2. A graphical representation of the adjustment paths or scenarios to be considered in the power study is provided in Figure 1.

[Insert Figure 1]

First, a "sudden" jump (alternative hypothesis (H_{SJ})) corresponds with an instantaneous increase in the synchronization index from ρ_1 to ρ_2 at time $T/2$. Second, a "quick" increase (alternative hypothesis (H_{QI})) corresponds to a rise of the synchronization index of $\frac{4(\rho_2-\rho_1)}{T}$ per time unit, meaning that ρ_2 is reached at $3T/4$. Finally, a "slow" increase (alternative hypothesis (H_{SI})) corresponds to a rise of the synchronization index of $\frac{2(\rho_2-\rho_1)}{T}$ per time unit, which implies that ρ_2 is only reached at the end of the sample T. These three adjustment speed scenarios could be linked to the concepts of financial integration and contagion. Although there is not a clear unifying definition in the literature for either of these concepts, financial integration is usually associated with permanent but gradual changes in comovement measures whereas contagion is more associated with sudden but transitory shocks in the dependence structure of financial returns. A power study can clarify whether the test can distinguish gradual changes form sudden changes in the synchronization index.

The corresponding power results are reported in Table 2. The nominal size is again set to 5%. The power is only evaluated for the unrestricted version of the stability test.

[Insert Table 2]

The power is found to be small for changes in ρ that are either small or gradual (or both). The power is only of an acceptable magnitude for sudden, big changes in ρ. Indeed, it is surprising to see that the power rapidly worsens when the adjustment speed is lowered (even for large changes in ρ).

[17] This robustness result can be understood as arising from the heteroskedastic and autocorrelation consistent (HAC) nature of the variance-covariance matrix in the multivariate synchronization test and the stability test.

These results suggest that only suddenly occurring jumps can be detected which seems to exclude the financial integration interpretation for the breaks. Thus, we can safely conclude that breaks - if detected - provide evidence against gradual integration processes. However, the stability test cannot be considered as a full fledged contagion vs. integration test because it is unable to distinguish between permanent from transitory shocks.

4 Empirical evidence

In this section we apply the multivariate synchronization measure and accompanying stability test to Asian stock markets. We estimate full sample bivariate and multivariate synchronization indices for the stock market cycles of 5 East Asian countries. We also distinguish full sample and subsample results to identify temporal shifts in synchronization. The choice for Asian countries can be motivated by the fact that changes in the synchronization of stock market cycles are probably more likely to occur across emerging markets than across developed markets due to financial liberalization and recurrent financial turmoil. The full sample and subsample estimation results are complemented with a battery of tests. First, we test whether there is parameter variation in the full sample bivariate and multivariate synchronization indices. Second, we also run subsample homogeneity tests in order to determine whether the multivariate synchronization (homogeneity) hypothesis breaks down in subsamples. Nonrejection of the homogeneity hypothesis could be interpreted as evidence for "common" stock market cycles. If the common cycle hypothesis does not hold for all considered stock markets, it might still be the case that it holds for a narrower subset, i.e., an Asian "core". We therefore also pay attention to that possibility.

Us dollar-denominated and dividend-adjusted monthly stock market indices for Singapore (S), Thailand (Th), South Korea (K), Taiwan (T) and Malaysia (M) were downloaded from the IFS database over the period January 1985 until November 2005 which amounts to $T = 239$ monthly observations. Because the prime focus of the paper is a structural change analysis of cyclical stock market comovements, we did not try to maximize the number of countries but selected those Asian countries with the longest possible time series in the database. As we are interested in measuring the comovement of medium-run fluctuations or cycles across stock markets, we first have to identify these "bulls" and "bears". The cycle dummies are obtained by implementing the Bry and Boschan (1971) dating algorithm over a six month time interval. Previous studies seem to suggest that stock market cycle dating and the resulting cyclical comovement measures are relatively robust

across different types of (parametric, nonparametric) dating algorithms, see e.g. Candelon et al (2006). Figure 2 contains the evolution of the (log) stock indices for each of the countries, where the bull periods have been shaded to facilitate visual inspection.[18]

[Insert Figure 2]

It is striking to see that the 1st half of the sample almost primarily consists of bull periods which illustrates why investors have been talking about "Asian Tigers" for a long time. Also, the 1997 Asian crisis and its aftermath is clearly visible in the plots. More specifically, notice that our results replicate the earlier finding that financial crises seem to erupt several months into bear phases (and sometimes very close to the end), see e.g. Edwards et al. (2003).[19] However, and as Edwards et al. (2003, p. 936) rightfully pointed out, it would be premature to conclude on the basis of this observation only that bear markets are leading indicators of financial crises. Somewhat surprisingly, the dotcom bubble burst is also clearly visible despite the relative underrepresentation of technology companies in emerging markets. Last but not least, the figures provide casual evidence for comovement or "synchronization" between bull and bear periods across markets. In order to assess the degree of synchronization and whether it changed over time, we have to resort to the more advanced statistical tools introduced in the previous sections.

The cycle dummies $S_{i,t}$ $(i = 1, \cdots n; t = 1, \cdots, T)$ that result from applying the Bry-Boschan dating algorithm can now be used to calculate bivariate and multivariate synchronization indices $\widehat{\rho}$ over the entire sample period. These are reported in Table 3.

[Insert Table 3]

The GMM estimator of the full sample bivariate and multivariate synchronization index $\widehat{\rho}_0$ is calculated using eq. (4). As noted earlier the GMM estimator boils down to the Pearson correlation for bivariate cycle pairs whereas the multivariate synchronization indices stand for the restricted value of the bivariate Pearson correlation in higher dimensions provided the null hypothesis SMS(ρ_0) is not rejected, i.e., $W\left(\widehat{\rho}_0\right) \leq CV_W\left(95\%\right)$. The value for the

[18]The exact dates of the estimated peaks and troughs for each country are not reported in a separate table but are available upon request.

[19]For example, Korean and Thai stock markets already were in a bear phase prior to the Asian crisis for a considerable amount of time (three and one and a half years, respectively), see Edwards et al. (2003) and our own calculations.

test statistic and the critical value CV_W are also reported in the table.[20] The critical value is determined using a block bootstrap (see Appendix for further details on that procedure). Finally, the reported closed intervals $[\rho_-, \rho_+]$ contain all values of ρ_0 that lead to nonrejection of the null hypothesis of SMS(ρ_0). In order to better grasp the results in Table 3, consider e.g. the index of multivariate synchronization $\widehat{\rho} = 0.42$ for the triplet $[SING, THAI, KOR]$. The bivariate correlations for this triplet are of the same order of magnitude indeed. Thus, it should not surprise that the null hypothesis $\rho[SING, THAI] = \rho[SING, KOR] = \rho[KOR, THAI]$ cannot be rejected over the interval $[0.15, 0.69]$ which contains all three bivariate correlations. The nonrejection justifies the "restricted" 0.41 estimate and is obtained by minimizing the W-test over this interval.

If one compares the magnitude of synchronization indices in Table 3, the bivariate comovements seem to differ quite a lot at first sight, ranging from -0.04 (THAI, TAI) to 0.659 (all markets). However, the null hypothesis of a common stock market cycle (SMS(ρ_0)) can nearly never be rejected which justifies the reported multivariate synchronization estimates in the lower panels of Table 3. Those cases for which stock market cycles do not exhibit a common (homogeneous) correlation are denoted by "rej". Notice also that the polar cases $\rho = 0$ and 1 fall in the nonrejection intervals $[\rho_-, \rho_+]$ for only 7 out of 26 cases. This provides additional justification to allow for an "intermediate" estimation and testing procedure for "imperfect" multivariate synchronization.

We previously argued that cycle correlations - like the ones in Table 3 - are the more relevant risk diversification indicators provided investors base their buying and selling decision on how stock cycles evolve (i.e., if investors look at cycle turning points to time their buying and selling decisions). Moreover, the conventional correlations based on return pairs are found to be quite different for the majority of considered stock market pairs (not reported in the table). Otherwise stated, return correlations can provide misleading information about the potential for risk diversification when investors' time horizon (and thus their portfolio rebalancing) coincides with the stock market cycle.

We also want to know whether the cycle correlations in Table 3 are stable over the whole sample period. We earlier established (see Table 1 in simulation section) that the bootstrapped versions of the restricted and unrestricted test perform equally well in eliminating the size distortion. We therefore opt for the simpler unrestricted test procedure (the bivariate correlations in the

[20] Because it only makes sense to test for multivariate synchronization when $n > 2$, the columns for the W-test and the critical values are left empty in the bivariate panel.

parameter vector in eq. (6) are left unrestricted). Table 4 reports estimated break dates and corresponding values of the test statistic and the 95% critical value. Again, critical values CV_S are bootstrapped using the block bootstrap algorithm described in Appendix. Nonsurprisingly, the small sample critical values increase with the number of countries. This is consistent with the observation we made in the Monte Carlo section that size distortions of the asymptotic test increased with the number of countries. Moreover, the table shows that instability is generally present, both in bivariate and multivariate synchronization indices and that the majority of the breaks coincide with the Asian crisis era.[21]

[Insert Table 4]

Table 4 suggests that one should be very careful in interpreting the full sample correlations in Table 3 because they hide different subsample values. We therefore also calculated these corresponding subsample values because we also want to know the direction of the change in synchronization (the two-sided stability test does not provided us with that information). The subsample synchronization indices $\widehat{\rho}$ for the subsamples defined in Table 4 are reported in the final Table 5. Table 5 also contains subsample testing outcomes for the null hypothesis of imperfect multivariate synchronization using (4). If this subsample application of the W-test does not lead to rejections we are allowed to calculate multivariate synchronization indices for the subsamples. Evidently, we do not report subsample results for those markets whose multivariate synchronization index does not exhibit breaks according to the preceding table (see "no breaks" rows).

The most striking table feature is that the synchronization index in the 2nd subsample is nearly always much bigger than its pre-break counterpart.

[Insert Table 5]

Moreover, the pre-break nonrejection intervals are lower and do not overlap with the post-break nonrejection intervals. Both observations are consistent with the breakpoint outcomes of the previous table. The confidence

[21] If e.g. financial liberalization, the Asian crisis, or changes in exchange rate regimes are the main triggers of the synchronization breaks in Asia, one would expect a comparable importance of breaks in Latin American synchronization and a much smaller number of breaks for developed stock markets. We therefore also calculated the stability test for these two "control" groups of stock markets. The Latin American panel consists of Argentina, Brazil, Mexico and Chile whereas the European panel contains the UK, Germany, France, Italy, Netherlands, Belgium and Spain. We found significant breaks for nearly all Latin American synchronization combinations. In contrast, European synchronization was found to be remarkably stable. The results are omitted for sake of space considerations but are available upon request.

intervals actually suggest that pre-break synchronization was often insignificantly different from zero whereas post-break synchronization was perfect ($\rho = 1$) for more than half of the cases. Nonsurprisingly, the full sample synchronization index lies somewhere in between the subsample values and can be considered as a rough average of the true subsample values. Turning to the outcomes of the subsample homogeneity test, we only find a limited number of rejections for the 1st subsample; but deviations from homogeneity all disappear in the 2nd subsample. Thus, the multivariate synchronization index increases over time and heterogeneity - present in the 1st subsample on a limited scale - almost completely disappears after the breaks.

The observed increases in cyclical correlations suggest that the room for risk diversification drastically diminished after the Asian crisis (at least for portfolio managers that solely invest in the considered Asian markets and who buy and sell according to the turning points of the stock market cycle). If the increased synchronization persists in the long run (i.e. a permanent change) than the investors' (long run) "strategic" asset allocation will be affected whereas if the rise is transitory it will only affect their "tactical" asset allocation (portfolio compision in the short run). Insofar as the rise in stock market synchronization is permanent, regulatory authorities in the different countries probably have to adjust financial regulation in order to preserve banking system stability in the Asian financial system. More specifically, a high cross country stock market synchronization can lead to boom-bust credit cycles spilling over from one country to the other.

On the other hand, if the increased synchronization is a purely contagious and short run phenomenon, policy makers cannot do much more than (i) to prevent these spillovers by preventing the development of boom-bust cycles in their domestic economies and (ii) to mitigate the financial and real effects of the contagion if bulls and bears spillover to other markets.

Whether the increase in Asian stock market synchronization has a permanent or transitory character is open to debate. As a matter of fact, our current econometric framework is not able to disentangle whether the increase in stock market synchronization is permanent or transitory. Indeed, notice that the sheer magnitude of the subsample changes $\widehat{\rho}_2 - \widehat{\rho}_1$ is comparable to the largest synchronization changes assumed in the Monte Carlo power study. The magnitude of the jump and the inability to detect gradual breaks (see simulation section) suggest that the breaks and corresponding subsample results in tables 4 and 5 provide evidence against financial integration. However, the observed sudden rises in synchronization are not necessarily interpretable as evidence pro "financial contagion". The latter phenomenon would require, inter alia, that the jump in the correlations is only temporary.

5 Concluding remarks

In this paper we proposed a Generalized Method of Moments (GMM) framework to measuring the degree of synchronization between stock market "bulls" and "bears". We argued that an assessment of cycle duration and cycle comovement is potentially relevant for investors that base their investment decisions on the turning points of the stock market cycle. Moreover, policy makers and regulators might be interested to know the magnitude of stock market synchronization and whether it changed over time because of the potentially destabilizing effects for stock market bulls and bears on the real economy.

Prior to calculating a measure of cyclical synchronization we classified stock prices into "bull" and "bear" periods using the Bry and Boschan (1971) dating algorithm. We subsequently extended the Harding and Pagan (2006) framework in several directions.

First, we allowed for a value of the common synchronization index between -1 and 1 whereas Harding and Pagan only tested against the benchmark cases of complete perfect synchronization or nonsynchronization (so, they did not really estimate a common synchronization index but restricted it to either 0, -1 or +1 prior to performing the test for a common cycle). However, in practice, business cycles as well as financial cycles are neither perfectly synchronized nor completely independent which implies that our testing framework is closer to reality than Harding and Pagan's. Moreover, our approach also produces an estimate of the multivariate synchronization index ρ_0 ($-1 < \rho_0 < 1$).

Second, we proposed an endogenous stability testing procedure for detecting structural change in the cyclical stock market synchronization index ρ_0. Before putting the test at work in an empirical application, we performed a Monte Carlo experiment to evaluate the (small sample) size and power properties of the novel testing procedure. We found that the stability test suffers from massive overrejection when one uses asymptotic critical values and when the number of stock markets considered grows large. However, a bootstrap of the small sample distribution can remedy this problem fairly easily. In the power study, we made use of the small sample critical values such as to obtain size-adjusted power values. We found that the stability test is able to detect breaks reasonably well provided the changes in synchronization have a sudden character and are relatively large in magnitude. Indeed, the power deteriorates surprisingly quickly upon lowering the adjustment speed or decreasing the change in the synchronization index. Otherwise stated, the stability test seems unable to pick up gradual structural breaks in synchronization which means that a financial integration interpretation for

breaks is likely to be wrong in our framework. It is then tempting to interpret the breaks as evidence for financial contagion. However, one should be cautious with that break interpretation because the stability test is unable to distinguish permanent shocks from transitory shocks and contagion is by definition a transitory phenomenon.

Changes in the synchronization of stock market cycles are probably more likely to occur across emerging markets than across developed markets due to financial liberalization and recurrent financial turmoil. We therefore selected a set of Asian stock markets for our empirical application. Upon applying the stability test, we detected an increase in synchronization, mainly after the Asian crisis, that is both economically and statistically significant. Upon applying the test for multivariate synchronization on the subsamples defined by the breaks, the pairwise (bivariate) synchronization indices seem to converge even more towards each other after the break. Moreover, we were unable to find breaks for a control group of developed countries which seems to confirm that forces like financial liberalization, institutional reform and market turbulence like the Asian crisis - that have been less prminent in developed markets - might be responsible for the increased synchronization.

The observed rise in Asian stock market synchronization implies that there is less space for diversifying risk after the Asian crisis (at least for investors that solely invest in the considered Asian markets and whose portfolio rebalancing is dictated by the turning points of the stock market cycle). If the rise in stock market synchronization has a lasting character, regulatory bodies probably need to change their supervisory framework in order to preserve banking system stability in the Asian financial system. On the other hand, if the stronger comovements between bulls and bears is a purely transitory (and possibly contagious) phenomenon, policy makers cannot do more than (i) preventing these spillovers by reducing the potential for the build up of boom-bust cycles in their domestic economies and (ii) reducing the financial and real effects of the transitory shock if bulls and bears spillover to other markets.

The observed post-break increases in synchronization possibly contain both a permanent as well as a transitory component. First, one could imagine that the Asian crisis and its direct aftermath had a contagious character as many authors claimed since then. Subsequently, policymakers and regulatory bodies implemented a myriad of measures but the recepees for both dampening the effects of the Asian crisis and reducing the potential of a future potential crises to strike again and spread across borders were pretty similar in all affected countries. This "convergence" in post-crisis policy measures might itself have had a long run impact on the synchronization correlation. Disentangling the observed rise on synchronization correlations

into a permanent and a transitory effect makes part of our future research agenda.

Appendix: Block bootstrap algorithm

Koenker and Machado (1999) argued that size distortions due to a large number of GMM moment conditions can be partly remedied by increasing the sample size T. However, this does not seem to be a realistic option in our case; our own simulations (not included in the tables) have shown that one needs time series of several thousands of observations in order to mitigate the size distortion. We therefore opt to bootstrap the small sample distribution of the test statistics (**??**) and (6). The asymptotic pivotality of both tests and the fact that they are continuous functions of sample moments are sufficient to ensure proper convergence of the bootstrapped critical values to the true asymptotic distribution, see e.g. Horowitz (2001).

Although suitable regularity conditions guarantee proper asymptotic convergence of the bootstrap, we also want to know whether the bootstrap works in small samples, i.e., whether the bootstrapped critical values are sufficiently size-corrected. We limit ourselves to an exposition of the bootstrap algorithm for the critical values of the multivariate synchronization test in eq. (**??**), the procedure for the stability test being completely analogous. For sake of convenience, we limit ourselves to study the performance of the bootstrap under the null hypothesis of Strong Multivariate Nonsynchronization (SMNS), i.e., $\mathrm{H}_0 : \rho_0 = 0$. (The same null was assumed for the stability test bootstrap). We set up a Monte Carlo cum bootstrap experiment that consists of the following steps:

1. Step MC1: Assume a particular DGP and a filter $\varphi(.)$. Draw a $T \times n$ matrix by using either DGP_1 (IID returns) or DGP_2 (Bollerslev's Constant Conditional Correlation model). This renders the $T \times n$ matrix X.

2. Step MC2: Use the Bry-Boschan dating algorithm to build a $T \times n$ binary variable matrix S with characteristic element $\varphi\left(X_{i,t}^{MC}\right) = S_{i,t}^{MC}$.

3. Step MC3: Compute the simulated W-statistic for $\rho_0 = 0$, i.e., $W^{MC}(\rho_0 = 0)$ using S as input.

4. Step BO1: Generate a $T \times n$ matrix of bootstrap replications S^B with block length 25 in the time series dimension.

5. Step BO2: Compute the bootstrapped W-statistic for $\rho_0 = 0$, i.e., $W^B(\rho_0 = 0)$ using S^Bas input.

6. Repeat the bootstrap steps 4-5 a "sufficient" number of times (M). M is endogenously determined using the three step-method of Andrews and Buchinsky (2000).[22] A critical value is then obtained as the α percent quantile, say W^B_{crit} , from the empirical distribution of the bootstrap test statistic. The nominal size is set to $\alpha = 5\%$. The null hypothesis of $SMS(\rho_0 = 0)$ is rejected if $W^{MC}(\rho_0 = 0) > W^B_{crit}$.

7. Repeat steps $MC1$ to $MC3$, and $BO1$ to $BO3$ a large number of times to obtain the rejection frequencies of the test $W(\rho_0 = 0)$.

We opted for bootstrapping in blocks (BO1) because we know that the binary time series $S_{i,t}$ $(i = 1, \cdots, n)$ that constitute the columns of S can be described by higher order stationary and ergodic Markov chains, see Harding and Pagan (2006, p. 62). The determination of the optimal block length is an ongoing point of discussion in the bootstrap literature. Hall et al. (1995) suggest to set $w = c.T^{1/4}$, with c a fixed parameter depending on the DGP. We found by trial and error that the size distortion is best tackled with block lengths of size 25.

[22]The endogenous number of bootstrap replications M was found to vary between 200 and 2,000.

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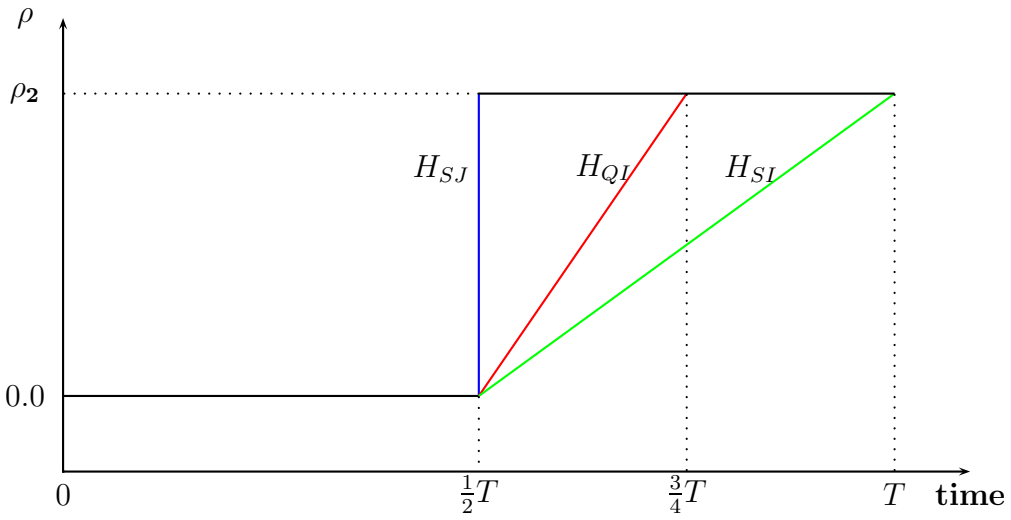
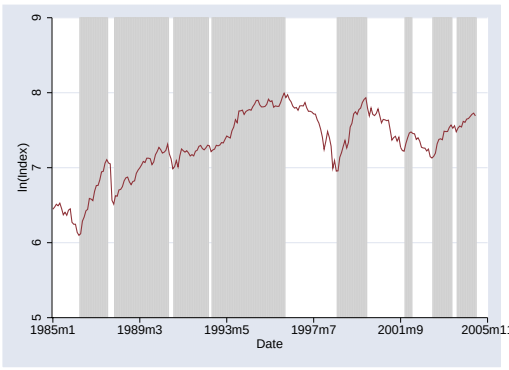
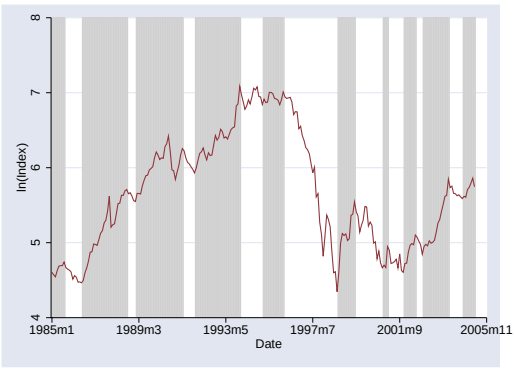
Figure 1: Alternative adjustment speeds for changes in synchronization

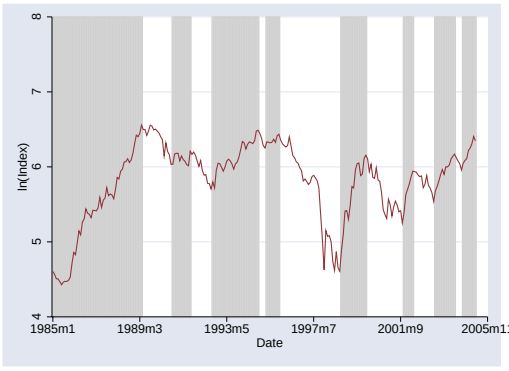




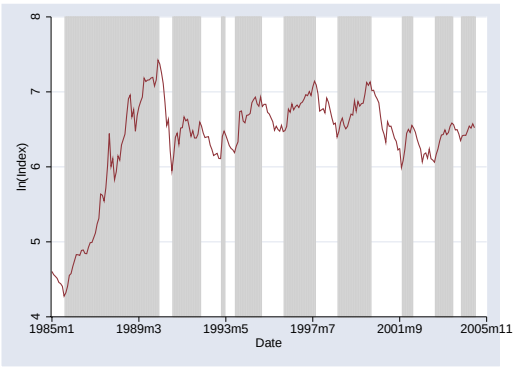
(a) Singapore



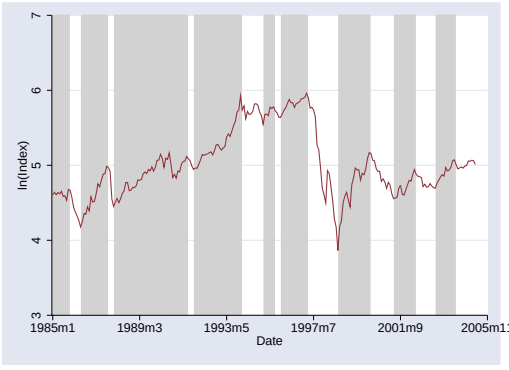
(b) Thailand



(c) Korea



(d) Taiwan



(e) Malaysia

Figure 2: Stock Indices and Bulls and Bears Classification

Table 1: Full sample cyclical stock market synchronization in South East Asia: estimates and homogeneity tests

country sets	$\widehat{\rho}$	$[\widehat{\rho}_-, \widehat{\rho}_+]$	$W(\widehat{\rho})$	CV_W
		Panel A: n=2		
$SING; THAI$	0.43	$[0.18, 0.68]$	-	-
$SING; KOR$	0.47	$[0.15, 0.79]$	-	-
$SING; TAI$	0.34	$[0.03, 0.66]$	-	-
$SING; MAL$	0.33	$[0.02, 0.65]$	-	-
$THAI; KOR$	0.31	$[0.03, 0.59]$	-	-
$THAI; TAI$	-0.04	$[-0.36, 0.27]$	-	-
$THAI; MAL$	0.43	$[0.16, 0.69]$	-	-
$KOR; TAI$	0.40	$[0.33, 1]$	-	-
$KOR; MAL$	0.26	$[0.23, 1]$	-	-
$TAI; MAL$	0.22	$[-0.10, 0.54]$	-	-
		Panel B: n=3		
$SING; THAI; KOR$	0.42	$[0.15, 0.69]$	2.81	14.14
$SING; THAI; TAI$	-	-	26.51	18.92
$SING; THAI; MAL$	0.42	$[0.12, 0.72]$	0.81	18.71
$SING; KOR; TAI$	0.41	$[0.10, 0.73]$	0.68	14.25
$SING; KOR; MAL$	0.38	$[0.03, 0.74]$	2.79	18.40
$SING; TAI; MAL$	0.31	$[-0.07, 0.69]$	1.39	18.78
$THAI; KOR; TAI$	-	-	24.58	15.44
$THAI; KOR; MAL$	0.37	$[0.07, 0.66]$	1.33	18.34
$THAI; TAI; MAL$	0.32	$[0.14, 0.51]$	12.99	19.87
$KOR; TAI; MAL$	0.33	$[-0.01, 0.67]$	2.31	18.18
		Panel C: n=4		
$SING; THAI; KOR; TAI$	0.61	$[0.52, 0.70]$	31.96	36.79
$SING; THAI; KOR; MAL$	0.42	$[0.09, 0.75]$	6.29	35.33
$SING; THAI; TAI; MAL$	0.53	$[0.39, 0.67]$	30.58	38.44
$SING; KOR; TAI; MAL$	0.39	$[0.00, 0.79]$	5.35	32.23
$THAI; KOR; TAI; MAL$	0.50	$[0.32, 0.69]$	26.20	42.73
		Panel D: n=5		
ALL	0.60	$[0.36, 0.84]$	36.78	81.90

Note: $\hat{\rho}$ stands for the estimated common synchronization index. The interval $[\rho_-, \rho_+]$ is the corresponding 95%confidence interval for $\hat{\rho}$. $W(\hat{\rho})$ is the test statistic for the $SMS(\hat{\rho})$ hypothesis (test of "multivariate synchronization" or "homogeneity"). CV_W stands for the 95% critical value of the bootstrap version of the test. The bootstrap is performed on the binary series in blocks of length 25. In the bivariate case $n = 2$, tests for multivariate synchronization cannot be performed because there is only one bivariate correlation.

Table 2: Testing for structural change in multivariate synchronization index

country sets	$\widehat{b}\,(m/yy)$	$\sup\left\{S_T(\widehat{b})\right\}$	$\mathrm{CV}_S\,(95\%)$
	Panel A: n=2		
$SING;THAI$	no break	7.91	11.94
$SING;KOR$	4/92	37.53	13.28
$SING;TAI$	8/97	18.13	12.03
$SING;MAL$	no break	2.97	11.21
$THAI;KOR$	10/94	18.86	12.32
$THAI;TAI$	8/97	23.38	11.76
$THAI;MAL$	no break	6.75	12.76
$KOR;TAI$	8/97	26.97	13.16
$KOR;MAL$	3/97	18.47	11.87
$TAI;MAL$	8/97	22.68	11.76
	Panel B: n=3		
$SING;THAI;KOR$	7/92	171.24	80.45
$SING;THAI;TAI$	8/97	141.32	82.28
$SING;THAI;MAL$	no break	28.00	84.09
$SING;KOR;TAI$	8/97	176.38	90.76
$SING;KOR;MAL$	7/92	196.61	87.16
$SING;TAI;MAL$	8/97	220.95	80.49
$THAI;KOR;TAI$	8/97	209.23	80.61
$THAI;KOR;MAL$	10/94	87.72	84.34
$THAI;TAI;MAL$	8/97	227.97	82.06
$KOR;TAI;MAL$	8/97	250.17	79.98
	Panel C: n=4		
$SING;THAI;KOR;TAI$	-	-	-
$SING;THAI;KOR;MAL$	9/92	391.94	341.42
$SING;THAI;TAI;MAL$	10/97	508.59	326.04
$SING;KOR;TAI;MAL$	8/97	715.33	356.26
$THAI;KOR;TAI;MAL$	8/97	713.89	353.77
	Panel D: n=5		
ALL	-	-	-

Note: The nominal size of the stability test is set to 5%. Table entry n refer to the number of countries. $sup\left\{S_T(\widehat{b})\right\}$ is the statistic associated with the structural break test and $CV_S\,(95\%)$ is the corresponding bootstrapped critical value at 95%. The bootstrap is performed on the binary series in blocks of length 25. The date of break is indicated in the column $\widehat{b}\,(m/yy)$. The stability test could not be adequately performed because of the near-singular character of the variance-covariance matrix for those case that are indicated with (-)

Table 3: Subsample cyclical stock market synchronization in South East Asia: estimates and homogeneity tests

country sets	subsample 1				subsample 2			
	$\widehat{\rho}_1$	$[\widehat{\rho}_-, \widehat{\rho}_+]$	$W(\widehat{\rho}_1)$	CV_W	$\widehat{\rho}_2$	$[\widehat{\rho}_-, \widehat{\rho}_+]$	$W(\widehat{\rho}_2)$	CV_W
Panel A: n=2								
$SING; THAI$				no break				
$SING; KOR$	-0.26	$[-0.55, 0.03]$			0.76	$[0.61, 0.92]$		
$SING; TAI$	-0.01	$[-0.46, 0.44]$			0.74	$[0.48, 1]$		
$SING; MAL$				no break				
$THAI; KOR$	-0.21	$[-0.48, 0.08]$			0.54	$[0.26, 0.82]$		
$THAI; TAI$	-0.46	$[-0.53, -0.39]$			0.45	$[0.06, 0.85]$		
$THAI; MAL$				no break				
$KOR; TAI$	0.04	$[-0.39, 0.46]$			0.87	$[0.73, 1]$		
$KOR; MAL$	-0.16	$[-0.41, 0.08]$			0.62	$[0.23, 1]$		
$TAI; MAL$	-0.21	$[-0.49, 0.06]$			0.65	$[0.24, 1]$		
Panel B: n=3								
$SING; THAI; KOR$	-0.14	$[-0.47, 0.18]$	2.58	41.49	0.73	$[0.51, 0.95]$	6.13	25.61
$SING; THAI; TAI$	rej.	rej.	116.84	27.17	0.70	$[0.32, 1]$	4.16	30.42
$SING; THAI; MAL$				no break				
$SING; KOR; TAI$	0.08	$[-0.30, 0.46]$	0.74	31.38	0.89	$[0.66, 1]$	5.86	34.57
$SING; KOR; MAL$	-0.01	$[-0.14, 0.13]$	10.56	29.50	0.84	$[0.69, 1]$	18.57	40.22
$SING; TAI; MAL$	-0.06	$[-0.30, 0.16]$	3.91	24.95	0.96	$[0.80, 1]$	14.90	39.78
$THAI; KOR; TAI$	rej.	rej.	58.11	29.82	0.85	$[0.65, 1]$	9.37	32.17
$THAI; KOR; MAL$	0.03	$[-0.05, 0.12]$	38.09	40.49	0.61	$[0.38, 0.83]$	10.94	22.95
$THAI; TAI; MAL$	rej.	rej.	160.27	25.73	0.77	$[0.49, 1]$	11.92	35.24
$KOR; TAI; MAL$	-0.09	$[-0.38, 0.19]$	2.40	25.87	0.85	$[0.58, 1]$	4.82	41.33
Panel C: n=4								
$SING; THAI; KOR; TAI$	-	-	-	-	-	-	-	-
$SING; THAI; KOR; MAL$	0.11	$[-0.07, 0.29]$	85.61	131.92	0.86	$[0.75, 0.97]$	34.59	59.81
$SING; THAI; TAI; MAL$	rej.	rej.	235.99	78.43	0.92	$[0.66, 1]$	27.31	129.10
$SING; KOR; TAI; MAL$	0.02	$[-0.25, 0.3]$	12.56	77.35	0.94	$[0.79, 1]$	16.72	131.78
$THAI; KOR; TAI; MAL$	rej.	rej.	336.52	76.39	0.85	$[0.5, 1]$	16.37	118.87
Panel D: n=5								
ALL	-	-	-	-	-	-	-	-

Note: Variables indexed by 1 (resp. 2) refer to the pre- (resp. post) break period. $\hat{\rho}$ represents estimates of the synchronization index and $[\rho_-, \rho_+]$ is the corresponding confidence interval at 95%. $W(\hat{\rho})$ is the test statistic of the $SMS(\hat{\rho})$ hypothesis and CV_W is the 95% critical value of the bootstrap version of the test. The bootstrap is performed on the binary series in blocks of length 25. Notice that in the bivariate case of $n = 2$ it exists only one synchronization correlation and then testing for $SMS(\hat{\rho})$ has no sense. The stability test could not be adequately performed because of the near-singular character of the variance-covariance matrix for those case that are indicated with (-) Therefore, reporting subsample results in those cases does not make sense. In the bivariate case $n = 2$, tests for multivariate synchronization cannot be performed because there is only one bivariate correlation.