Correlation in commodity futures and equity markets around the world: Long-run trend and short-run fluctuation

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Abstract

Addressing the view that recent hikes in the commodity-equity correlation will only be temporary, this paper differentiates itself from previous studies in two aspects: It examines the long-run trends and the short-run fluctuations of the commodity-equity correlation, and it does so to indices from 45 equity markets. Of them, 32 demonstrate an upward long-run trend in their correlations with the commodity futures market throughout the last decade, and 43 have had their correlation trends upswing sharply during the recent financial/economic turmoil. Conditional correlations of 39 equity markets with the commodity futures market move towards or above their long-run trends when volatilities of these equity markets increase. Our results constitute compelling evidence that the attenuating diversification benefits of commodity futures are a long-run and world-wide phenomenon.

Key words: commodity futures; equity; conditional correlation; long-run trend

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1. Introduction

"Despite recent history, commodities still provide portfolio diversification", asserted a web article, retailing the opinions of two researchers published in the *Financial Times*.[1] The bottom line of the underlying argument is that higher return correlations between commodity futures and equities observed since 2008 will be temporary and the correlations will revert to their historical low levels (zero or negative) over the long run. The argument explicitly dismisses all the studies published after 2008 which have reported sharp increases in the commodity-equity correlation in the recent past. This prompts us to conduct a further investigation and explore the question of whether rises in the correlations are only transitory. We do this to the correlations of 45 economies' equity markets with the aggregate commodity futures market.

Commodity derivatives, as an alternative financial asset class, have gained increasing importance. According to Basu and Gavin (2011), the ratio of the notional amount of commodity derivatives contracts to world GDP rose from 1.5% in 1998 to 21.6% in 2008, and the gross market value of commodity derivatives rose by a factor of 25 between June 2003 and June 2008 - reaching $2.13 trillion in June 2008. One of the most attractive attributes of commodity futures is widely believed to be their ability to offer diversification benefits to traditional financial portfolios comprising equities and bonds. Along this line, the academic literature on commodity futures covers a wide range from studying commodity futures markets to investigating individual futures contracts, and from the risk management perspective of portfolio diversification to the active strategies of abnormal return maximization.

Empirical evidence on commodity futures' diversification benefits is mixed. Research done before 2009 (or using data series that end in or prior to 2007) usually shows that return

[1] http://seekingalpha.com/article/187751-despite-recent-history-commodities-still-provide-portfolio-diversification

correlations between commodity futures and equities/bonds are on average very low, and superior risk-adjusted returns can be obtained by including commodity futures in portfolios consisting of stocks and bonds (Bodie and Rosansky, 1980; Bodie, 1983; Lee et al, 1985; Lummer and Siegel, 1993; Ankrim and Hensel, 1993; Kaplan and Lummer, 1998; Anson, 1999; Greer, 2000; Georgiev, 2001; Gorton and Rouwenhorst, 2006; and Chong and Miffre, 2010). On the other hand, several recent studies have challenged these findings. Silvennoinen and Thorp (2010), Tang and Xiong (2010), Daskalaki and Skiadopoulos (2011), and Büyükşahin et al (2010)[2] provide evidence that return correlations between commodity futures and equities have increased substantially during the recent subprime crisis. In addition, Cheung and Miu (2010) and Büyükşahin et al (2010) also find that the alleged diversification benefits do not exist when they are needed the most during the period of stock markets being highly volatile or the episode of financial crisis.

However, the evidence of recent sharp increases in the commodity-equity correlation is not yet convincing enough for reaching a conclusion that the long-term diversification value of commodity futures has vanished. Studies that provide such evidence all fail to touch a gut issue that the recent higher commodity-equity correlation can be a long-run, rather than a short-run, phenomenon. A question immediately follows: How do we address the issue?

Empirical macroeconomics suggests that an economic time series (e.g., GDP per capita) may comprise a secular component and a cyclical component. The former represents the long-run trend of the series, while the latter the short-run fluctuations of the series around its trend. Furthermore, large but rare shocks work to cause structural breaks in the trend component, while small and frequent shocks are the sources of the fluctuation component. Borrowing this idea, we make similar decomposition of a correlation series for careful anatomy. To the best of our

[2] Büyükşahin et al (2010) nevertheless argue that the increased correlstions were still lower than their peaks in the 1990s, and thus there was "no pesistent increase in co-movements between returns on passive commodity and equity investments over the course of the last 17 years".

knowledge, the present paper is the first to do so, which differentiates our study from any prior work on the commodity-equity correlation.[3] More importantly, it enables us to provide insights into the question of whether the recent hikes in the correlations are due to (1) increases in their trends or (2) upward deviations from their unchanged trends or (3) increases in their trends as well as upward deviations from their rising trends. If the results favour (1) or (3), one will be able to refute the assertion that "despite recent history, commodities still provide portfolio diversification", since a trend component is considered to be secular. If the results are in line with (2), the diversification benefits of commodity exposures as a long-term notion will still be a valid guide for strategic portfolio allocation between the commodity class (or commodity futures indices) and other asset classes such as stocks (equity indices).

The long-run trends of commodity-equity market correlations are likely to be governed by industrialization and financialization. Industrialization tends to increase commercial traders in commodity markets who use industrial commodity futures to hedge their business activities. Kilian and Park (2009) find that the real prices of crude oil and equities move upward in sync only during episodes of growth in world demand for industrial commodities. Financialization tends to increase non-commercial traders (financial investors) in commodity markets, such as hedge funds and commodity index funds, who use commodity futures to hedge equity and bond risk. Silvennoinen and Thorp (2010) suggest two ways in which financialization leads to increases in the correlation of commodity futures markets with conventional asset markets. One is by more and more investors holding both commodity securities and conventional financial assets, and the other is through higher and higher integration between commodity and conventional asset markets. In the former

[3] Silvennoinen and Thorp (2010) force conditional correlation between commodity futures and financial indices to change smoothly over time. They find that correlations between S&P500 returns and returns on many commodity futures have increased gradually from a much earlier date, similar to our findings. But, because of smoothing, the long-run trends and the short-run fluctuations of conditional correlation are mingled, rendering it difficult to pinpoint the source of correlation changes and to provide a clear-cut answer to questions concerning the *long-term* diversification value of commodity futures.

case, a shock originating in one market would swiftly spread across several markets, since they share a set of common state variables driving stochastic discount factors. In the latter case, systematic shocks would dominate commodity returns, raising the correlation of the commodity market with other asset markets. However, since financialization is a long-run trend, we assume, naturally, that financialization moves correlation by affecting its trend (secular) component. This differs from Silvennoinen and Thorp (2010) who treat correlation as a whole.

It then follows that when some shocks are "large" enough to impact, positively or negatively, the process of financialization, the trend component of the commodity-equity correlation should experience a structural break. The recent subprime mortgage crisis is an obvious example of such big shocks. Another example could be a surge of index investment in commodities. Tang and Xiong (2010) note that the increasing presence of index investors will precipitate a fundamental process of financialization among commodities markets, through which commodity prices become more correlated with prices of financial assets. Logically, if the increase in the index investment flow is sudden and of a large scale, there would be an upward jump of the correlation trend. Needless to say, large shocks originating from extreme events/episodes are rather rare, but once occurring they would cause upswings in the correlation trend.

The short-run fluctuations of commodity-equity market correlations are, on the other hand, likely to be driven by volatilities in the commodity futures market and the equity markets, among other things. See, for example, Silvennoinen and Thorp (2010) and Chong and Miffre (2010). However, our underlying assumptions differ from theirs: We consider that these volatilities impact correlation by affecting its fluctuation (cyclical) component. In other words, the short-run deviations of correlation from its trend should have to do with regular/frequent, "small" shocks such as volatilities. Note, it is likely that a cataclysmic shock will precipitate huge volatility which has both the trend-breaking effect and the fluctuation effect. In any event, however, by investigating the relation between the fluctuation component of correlation and volatilities in commodity and equity markets, we are able to address another question: Given the correlation trend, do the diversification benefits of commodities to equity investors exist when they are needed the most?

Recent studies have examined correlations between individual commodity futures and the indices of other financial asset classes (Silvennoinen and Thorp, 2010; Chong and Miffre, 2010; and Tang and Xiong, 2010) and correlations between commodity futures indices and equity indices from a limited number of developed markets such as US and Canada (Cheung and Miu, 2010). As the first attempt in the literature, we apply our approach outlined above to examining commodity-equity index correlations for 45 equity markets from developed and emerging economies, to obtain world-wide, at-the-market-level evidence regarding the question posed at the beginning of this introduction section. This international evidence is particularly valuable for several reasons.

First, it has been observed that the subprime crisis, originating in the US, spread more swiftly to Europe and North America due to a higher degree of their financial integration. Other economies, especially emerging markets, however, are relatively less integrated with the US. It is, therefore, interesting to see whether there are any differences across a broader set of equity markets in terms of the impact of the crisis on their correlations with the commodity futures markets.

Second, the diversification benefits of commodity futures may also vary across markets due to their different characteristics. For instance, Cheung and Miu (2010) uncover that since the resource-based sectors in the Canadian stock market are more important than those in the US stock market (See Cheung and Miu (2010) for what the “resource-based market” means), correlations between commodity futures indices and equity indices are higher for Canada than for the US. Such a difference, and many other differences, ought to exist beyond the US-Canada pair. In other words, the diversification benefits of commodities, if existent, could be country-specific. To this end, we seek evidence on the differences in the long-run trends of correlation by including as many equity markets as possible in our sample.

Third, the evidence should be relevant to those index investors who wish to invest in commodity futures indices and equity indices from different national stock markets, given that individual commodities are now found to have lost their diversification values. If the evidence is negative about commodity futures indices' diversification benefits, it may assist a number of bills introduced in the US that prohibit or limit the activities of commodity index traders (USS/PSI 2009).

We employ the dynamic conditional correlation (DCC) model to generate correlation series. An advantage of this model is that it does not smooth out fluctuations while also preserving trends. This well serves our conceived approach to anatomizing the secular and cyclical components of a correlation series.

The rest of this paper is organised as follows. Section 2 describes data and the methodology used. Section 3 presents and discusses empirical results. Section 4 concludes.

2 Data and Methodology

2.1 Data

We use the S&P Goldman Sachs Commodity Index (S&P GSCI) as the commodity futures index, for several reasons. It is a composite index of commodity sector returns representing an unleveraged, fully collateralized and long-only investment in commodity futures and is broadly diversified across the spectrum of commodities. The combination of these attributes provides investors with a reliable and publicly available benchmark for investment performance in the commodity markets comparable to the equity indices. Also, the S&P GSCI has been employed in most existing studies on commodity diversification effects, which makes our results comparable with theirs. Table A1 in Appendix 1 presents the index's components and their weights.

In order to provide world-wide evidence, we include 45 economies' equity indices in this work, and obtain them from the Morgan Stanley Capital International All Country World Investable Index (MSCI ACWI). The MSCI ACWI is a free float-adjusted, market-capitalization weighted index, and is designed to measure the equity market performance of developed and emerging markets. It consists of 24 developed and 21 emerging equity market indices. It also captures up to 98% of the developed and emerging investable market universe, covering over 9,000 large, mid and small cap securities in 45 countries. Table A2 in Appendix gives the index's components and their weights.

All data, sourced from DataStream, span from 1 January 2000 to 31 December 2010. We choose this sample period out of the following considerations. First, the last 11 years are the history that has witnessed a noticeable change in the commodity-equity correlation which largely dismantles the consensus based on earlier data that commodities can provide adequate portfolio diversification. Focusing on this recent history is to make our study topical. Extending the investigation period beyond 2000 would generate the results for the pre-2000 period that are already reported in many existing studies, which is therefore not our interest and concern. Second, data for some emerging markets, such as Indonesia and Morocco, are available only after 2000. Third, from the econometric point of view, 11 years of daily data (totalling 2,870 return observations) are long enough to yield meaningful estimation results without a serious problem of a small sample bias.

2.2 Generating conditional correlation series

When testing the diversification effect of a specific asset class, researchers often employ the conditional correlation framework (Büyükşahin, et al., 2010; Chong and Miffre, 2010; Kat and Oomen, 2006). We continue with this framework, and employ the DCC model of Engle (2002) to estimate time-varying return correlations between commodity futures and equities. This is because a recent work by Huang and Zhong (2010) reports that the DCC model outperforms other correlation structures, such as rolling-window, historical, and constant correlations.

According to the GARCH model (Bollerslev, 1986), a return series $r_{i,t}$ is generated by

$$r_{i,t} = u_{i,t} + \sqrt{h_{i,t}}\,\varepsilon_{i,t} \tag{1}$$

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{2}$$

where $u_{i,t}$ is the conditional mean that contains ARMA(p,q) terms of $r_{i,t}$ plus a constant, so that the demeaned return series will have *iid* standardized residuals $\varepsilon_{i,t}$ with a zero mean, and conditional variance of $h_{i,t}$. For the GSCI and the equity index return series, an ARMA(1,1) process is selected to mitigate autocorrelation.[4] Equation (2) is subject to $\omega_i > 0$, α_i and $\beta_i \geq 0$, and $\alpha_i + \beta_i < 1$.

The conditional correlation between commodity futures returns and equity index returns is estimated via DCC(1, 1) for their standardized residuals. According to Engle (2002), the conditional covariance matrix is expressed as $H_t = D_t R_t D_t$, where $D_t = diag\{\sqrt{h_{i,t}}\}$ is a diagonal matrix of univariate GARCH volatility, and R_t, the conditional correlation matrix for standardized residuals $\varepsilon_{i,t}$, is expressed as $R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}$. $Q_t = (q_{i,j,t})$ can be described by

$$Q_t = (1-a-b)\bar{Q} + a\left(\varepsilon_{t-1}\varepsilon_{t-1}^{'}\right) + bQ_{t-1} \tag{3}$$

Where $\bar{Q}$ is the $N*N$ unconditional covariance matrix of standardized residuals, a and b are non-

[4] Our trials showed that using higher-order ARMA processes to eliminate serial correlation in $\varepsilon_{i,t}$ does not affect qualitatively the results of DCC estimation based on ARMA(1,1).

negative coefficients subject to $a + b < 1$. $diag\{Q_t\} = \sqrt{q_{ii,t}}$ is a diagonal matrix containing the square root of the ith diagonal elements of Q_t, so the conditional correlation between asset i and j at time t can be written as $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$.

Taking into account the effects of the 2008 Financial Crisis on the return correlation between commodity futures and equities, we follow a method proposed by Li and Zou (2008) that allow for structural breaks in $\bar{Q}$. According to the National Bureau of Economic Research, the duration of the 2008 Financial Crisis is 18 months from December 2007 to June 2009. We thus consider two break dates: The first τ_1 is set as 1 December, 2007 and the second τ_2 as 1 July 2009. After modifying (3) accordingly, we have

$$Q_t = (1-a-b)\left(\bar{Q}_1 + \bar{Q}_2 + \bar{Q}_3\right) + a\left(\varepsilon_{t-1}\varepsilon_{t-1}^{'}\right) + bQ_{t-1} \tag{4}$$

Where $\bar{Q}_1$ is the unconditional covariance matrix for $t < \tau_1$ and set to zero otherwise; $\bar{Q}_2$ is the unconditional covariance matrix for $\tau_1 \leq t < \tau_2$ and set to zero otherwise; and $\bar{Q}_3$ is the unconditional covariance matrix for $t \geq \tau_2$ and set to zero otherwise. To make inference on the number of structural breaks, we conduct the log likelihood ratio (LRT) test on two successive cases. In case 1, the null hypothesis is $\bar{Q}_1 = \bar{Q}_2 = \bar{Q}_3 = \bar{Q}$ indicating no structural breaks, and the alternative hypothesis is $\bar{Q}_1 \neq \bar{Q}_2 = \bar{Q}_3$ implying one structural break. In case 2, the null is $\bar{Q}_1 \neq \bar{Q}_2 = \bar{Q}_3$ and the alternative becomes $\bar{Q}_1 \neq \bar{Q}_2 \neq \bar{Q}_3$, suggesting two structural breaks instead of one. The value of the log likelihood function generated from each case is used to compute the likelihood ratio test statistic which is then used to decide whether or not to reject the null in favour of the alternative in the two cases respectively.

2.3 Decomposing conditional correlation series

Our approach to studying the DCC-generated conditional correlations is distinct from previous studies (e.g., Chong and Miffre, 2010) where the correlations are simply regressed on conditional return volatilities of equities and commodity futures. Specifically, we decompose a correlation series into a trend component and a deviation-from-trend component (hereafter a deviation component for short): $\rho_t = TREND_t + DEV_t$. The trend component ($TREND_t$) describes the long-run evolutionary behaviour of a correlation series, and is assumed to be subject to rare but cataclysmic shocks such as the 2008 global crisis. The deviation component (DEV_t) delineates the short-run fluctuations of the correlation series around its trend, and is assumed to be perturbed by regular shocks such as volatilities from commodity futures and equity markets. In other words, we assume that infrequent "large" shocks impact $TREND_t$ only, causing its break, while frequent "small" shocks affect DEV_t only, causing deviations from trend.

Before estimating the secular (trend) component, it is necessary to make sure that a de-trended series (i.e., the cyclical component) is stationary (referred to as trend stationary). An econometric method for this purpose is to conduct multiple-break unit-root tests. In the literature (See Li, 2005, and the references therein), the number and the date(s) of break(s) can be treated as unknown (endogenous) or known (exogenous). If unknown, searching for break dates/numbers over all time points is inevitable, and will entail huge computational burden where the sample size is large. Our sample size (2,870 observations × 45 series) is certainly too large to make searching tractable. Fortunately, we have information sufficient enough to treat structural change as known, or to impose exogenously the break number/dates, the information coming from or already used in the estimation of the DCC model.

The unit-root test for $\phi_2 = 0$ is performed for the 45 correlation series in the following regression:

$$\Delta\rho_t = \phi_0 + \phi_1 T + \phi_2 \rho_{t-1} + \phi_3 D_{1,t} + \phi_4 D_{2,t} + \sum_{s=1}^{n} \psi_s \Delta\rho_{t-s} + \upsilon_t \quad (5)$$

where ρ_t, a series of conditional correlations between commodity futures and equity returns, is obtained via the DCC model outlined in the preceding section. $D_{1,t}$ and $D_{1,t}$ are the two dummy variables (if the number of detected structural breaks in the DCC model is two). $D_{1,t}$ equals one for 1 December 2007 through to 31 December 2010 and zero otherwise. $D_{2,t}$ equals one for 1 July 2009 through to 31 December 2010 and zero otherwise. However, if the LRT indicates that the number of break is 1, $D_{2,t}$ will be dropped from (5); and if the LRT indicates no break at all, both $D_{1,t}$ and $D_{2,t}$ will be dropped. T denotes a time trend. Where the estimate of ϕ_1 is insignificant, T will be deleted from (5). Adding $\Delta\rho_{t-s}$ to (5) is to remove possible autocorrelation in υ_t. In determining the truncation lag length n, we employ the so-called "t-sig" method described in Perron (1994). Briefly speaking, the t-sig procedure is as follows: Start with $n = n_{max}$ and then reduce n from n_{max} by 1 at a time, till the absolute value of the t-statistic on ψ_n is greater than or equal to 1.6, the 10% value of the asymptotic normal distribution. $n_{\max}$ is set at 5 in this paper. In cases where ψ_5 is significant at the 10% level, we increase n^* to 6 but find that ψ_6 becomes insignificant at this level.

For statistical inference on trend-stationarity, we compute the exact finite-sample distributions of the test statistics on the significance of ϕ_2 for the 45 series through Monte Carlo simulations, following the bootstrap method as suggested in Zivot and Andrews (1992). The model used for Monte Carlo simulations is identical to (5) which, however, may vary across the 45 different markets, depending on the number of breaks (2, 1 or 0), on whether T is included in (5), and on the truncation lag length n determined.

If a correlation series is found to be trend-stationary, we proceed to estimate its trend component in two steps. The first is to run regression as follows:

$$\rho_t = \mu + c_0 T + c_1 D_{1,t} + c_2 D_{2,t} + \sum_{k=1}^{m} d_k \rho_{t-k} + e_t \tag{6}$$

All the variables in (6) are defined the same as in (5). Again, whether $D_{1,t}$ and/or $D_{2,t}$ should be included is determined by the LRT test as already discussed above for (5). A positive (negative) estimate of c_1 indicates that, other things being equal, the return correlations were higher (lower) during the 2008 financial crisis than before. If c_2 is estimated to be positive (negative) where $D_{2,t}$ is present, this means that, given everything else, the return correlations increased (decreased) after the crisis from those during the crisis. Adding ρ_{t-j} to (6) is, again, to remove autocorrelation in e_t. m is determined in the same way as n.

The second step is to use the coefficient estimates $\hat{\mu}$, $\hat{c}_0$, $\hat{c}_1$ (where $D_{1,t}$ is present), $\hat{c}_2$ (where $D_{2,t}$ is present), $\hat{d}_1,\ldots,\hat{d}_m$ yielded by (6) to compute the trend component known as the fitted trend function as follows:

$$TREND_t = \hat{\tau}_0 + \hat{\tau}_1 T + \hat{A}(L)^{-1}\left(\hat{c}_1 D_{1,t} + \hat{c}_2 D_{2,t}\right) \tag{7}$$

where $\hat{\tau}_o = \dfrac{\hat{\mu} - \hat{c}_0 \sum_{k=1}^{m} k\hat{d}_k}{1 - \sum_{k=1}^{m} \hat{d}_k}$, $\hat{\tau}_1 = \dfrac{\hat{c}_0}{1 - \sum_{k=1}^{m} \hat{d}_k}$ and $\hat{A}(L) = 1 - \sum_{k=1}^{m} \hat{d}_k L^k$ with L being the lag operator.

By definition, the deviation component is measured by $DEV_t \equiv \rho_t - TREND_t$. We next run the following regression to investigate whether and how volatilities in commodity futures and equity markets move their correlation away from its trend:

$$DEV_t = \delta_0 + \delta_E \sqrt{h_{E,t}} + \delta_C \sqrt{h_{C,t}} + \xi_t, \quad \xi_t = z_t + \sum_{i=1}^{q} \theta_i \xi_{t-i} \tag{8}$$

where $\sqrt{h_{E,t}}$ and $\sqrt{h_{C,t}}$ represent respectively the volatility of equity index returns and the volatility of commodity futures index returns. We assume that the error terms ξ_t follow an AR(q) process, and so employ the HILU procedure (Hildreth and Lu, 1960) to estimate (8). The OLS estimation without allowing for autocorrelation in the error terms would lead to the problem that the coefficient estimates are inefficient, the standard error estimates are underestimated, and the value of R^2 is overestimated. This problem plagues previous studies such as Chong and Miffre (2010).

3. Empirical Results

3.1 Preliminary analysis of correlation

Table 1 sets out the coefficients of return correlations between GSCI and equity indices for developed markets, as well as *t*-values for comparing their statistical significances. As reviewed in Introduction, earlier studies have reported that return correlations between commodity futures and equity indices (mainly from the US) before the new millennium were close to zero or even negative. According to columns 2 and 3 of Table 1, however, the commodity-equity return correlation for 24 developed markets over the period 2000-2010 are all positive and significant at a higher than the 1% level, ranging from 0.103 for Israel to 0.399 for Canada.

To see the effects of the 2008 financial crisis on correlations, columns 4-7 of Table 1 calculate correlation coefficients for the pre- and during-/post-crisis periods. Before the crisis (2000-2007), return correlations were relatively low, ranging from -0.011 for the US to 0.182 for Canada, and many coefficients are also much less significant statistically. Since the crisis broke out (2008-2010), all return correlations have increased considerably, with the highest (0.62) for Canada and the lowest (0.14) for Japan, and their statistical significances have also risen dramatically as compared to column 5. The results from the two sub-sample periods indicate that diversification benefits from adding the commodity futures to equity portfolios have attenuated substantially since 2008.

Table 1 also reveals some other interesting findings. Among all developed markets, the correlation between the commodity futures market and the Canadian equity market is always the highest, followed by the return correlation involving the Norwegian equity market as the second highest. The relatively high return correlations may be due to both countries' equity markets having their lion's share go to commodity-related companies. The combination of energy and material sectors represents 48% of the total capitalization of the TSX 60 stock index in Canada (Standard & Poors Financial Services, 2010), and represents nearly 40% of the total capitalization of the Norwegian stock market (Oslo Børs, 2010). These results are consistent with the finding of Cheung and Miu (2010) that commodity futures offer less diversification benefit to resource-based markets.

Table 2 concerns emerging equity markets in terms of their correlations with the commodity futures market. Regarding the impact of the 2008 financial crisis on the correlation coefficients, we observe similar pictures to those of developed equity markets. The 21 correlation coefficients are clearly much higher for the post-crisis period (2008-2010) than for the pre-crisis period (2000-2007), and the same can be said about their statistical significances.

Comparing Table 1 with Table 2 conveys additional messages worth noting. Even though the 2008 Financial Crisis has led to significant increases in the return correlations between the commodity futures market and both developed and emerging equity markets, the magnitude of the increases is greater for the former than for the latter. Moreover, since 2008, the Southeast Asian equity markets appear to have had relatively lower return correlations with GSCI than their European and American developed and emerging counterparts. This may indicate that the 2008 crisis has afflicted the European and American equity markets more strongly than the Southeast Asian equity markets.

The evidence that the commodity-equity return correlation has risen significantly since the 2008 crisis is not new albeit worldwide for the first time in the literature. We regard it only as the result of our preliminary analysis, and take a step forward to address the questions not examined in any previous work: Has the commodity-equity correlation changed only since the 2008 financial crisis? If not, how have they evolved over time during the last 11 years and in what direction? Asking these questions aims at the belief that, despite recent history, commodities still provide portfolio diversification if viewed from a long-run perspective.

3.2 Long-run trend of correlation

We estimate the DCC model merely to obtain observations on the time series of conditional correlations. The estimates of the GARCH and DCC parameters are not very interesting and so are placed in Appendix (See Tables A4 and A5 in Appendix. Table A3 in Appendix provides summary statistics for the 46 returns series used in estimating the DCC model). However, the test results for structural break are directly relevant to, or determine largely, our main results to be discussed late on. So, they are reported in Table 3 in the main text.

Based on Table 3, we follow the following rules in making inference about structural break in conditional correlation. First, if the null of no break and the null of 1 break are both rejected in favour of the alternative of 2 breaks, the correlation is considered to have 2 breaks. Second, if the null of no break is rejected in favour of the alternative of 1 break, but the null of 1 break cannot be rejected in favour of the alternative of 2 breaks, the correlation is considered to have 1 break. Third, if imposing two breaks would lead to a smaller log likelihood function than imposing 1 break, the correlation is consider to have 1 break. This case is represented by "-". Finally, if the null of no break cannot be rejected in favour of the alternative of 1 break and the alternative of 2 breaks, and the null of 1 break cannot be rejected in favour of the alternative of 2 breaks, the correlation is considered to have no break. Canada and Norway are the only two examples of this case. The numbers of breaks so determined are presented in the last column of Table 3.

Table 4 presents the results of test for trend stationarity, with the numbers of structural breaks detected in Table 3. For the sake of space conservation, we only report the estimate of ϕ_2 associated with ρ_{t-1} in (5). Using the critical values obtained via simulations, the null hypothesis of non-stationarity is rejected at the 5% level for two correlation series (Brazil and Canada), and at the 1% level for the remaining 43 series. We therefore infer that the 45 correlation series are all stationary with respect to their trends. Or simply put, the cyclical component (short-run fluctuations) is stationary for all the 45 conditional correlation series. This suggests that the secular components estimated via equations (6) and (7) capture the long-run evolution paths to which correlations will revert before long.

Table 5 reports the estimation results of equation (6). The coefficient estimate ($\hat{c}_1$) of the first-break dummy is positive and statistically significant (at a higher than 5% level) for all markets but Canada and Norway.[5] This suggests that an overwhelming majority of national equity markets have been affected by the burst of the 2008 financial crisis in terms of their correlations with the commodity futures market. To illustrate, take Philippines as an example. Its $\hat{\mu}$ is estimated to be 2.592 (%), and its $\hat{c}_1$ 5.189 (%). This means that, even if all other things were held constant, the correlation between the Philippine equity market and the commodity futures market rose by 5.189 percentage points to 7.781% due to the cataclysmic shock.

However, this is not the end of the story of rising commodity-equity correlations. Surprisingly, after the 2008 financial crisis is deemed to be over, the correlations further increase, rather than fall or remain unchanged, for more than half of the markets under investigation.

[5] Variables (excluding the intercept) with coefficient estimates statistically insignificant at the 10% level are dropped before re-estimation of (6). A zero value of the corresponding coefficient is then used in (7) to compute the fitted trend function.

Specifically, the coefficient estimate ($\hat{c}_2$) of the second-break dummy is positive and statistically significant (at a higher than 5% level) for 26 out of 45 markets. The remaining 19 markets' $\hat{c}_2$ are imposed a zero value, since Table 3 suggests only one break for 17 of them and no break for two of them.

The time-trend coefficient estimate ($\hat{c}_0$) is positive and statistically significant (mostly at a higher than 5% level) for 32 out of 45 markets. This indicates that the 32 markets had their commodity-equity return correlations grow over time in the past 11 years. Among those without a significant time trend in the correlations, 10 are emerging economies and 3 developed (Japan, New Zealand and the US).

An additional message from Table 5 is that conditional correlations between the GSCI and equity index returns are very persistent, with none of the 45 equity markets being an exception. This is evidenced by highly significant estimates of the d_1 coefficient for them all, plus highly significant estimates of some of the other d coefficients for some of them. Such strong persistence in the correlation series urges us to avoid directly applying the OLS method in regressing the correlation series against other variables, as this would cause serial correlation in the regression residuals and so yield inefficient and biased coefficient estimates.

We are now ready to conduct graphical analysis of the trend component of correlation. This shall give us a more intuitive picture about how the 45 conditional correlation series evolve over time along their long-run path. Figure 1 contains 45 panels each plotting a conditional correlation series and its fitted trend function obtained by plugging the coefficient estimates from Table 5 into equation (7). Several messages from Figure 1 warrant discussion.

The first and the foremost observation is that 71% (or 32 out of 45) of our sample markets demonstrate positive slopes of their correlation trend functions. Of the steepest slopes seem to be Canada, Norway and Peru. The 32 trend functions begin with a value close to zero, indicating low long-run correlations at the arrival of new millennium. However, since then, the 32 correlations have evolved over time around ever increasing trend values, suggesting that diversification benefits coming from commodity futures have constantly attenuated. Put differently, that the long-run (as opposed to the short-run) values of the correlations have kept trending up is not "recent history". Thus, it would have been reasonable to expect the upward trends to continue beyond 2007 even if the global financial turmoil had not happen between December 2007 and June 2009.

Unfortunately, the financial crisis did happen but in the way to abruptly and considerably raise the values of 43 out of 45 trend functions, including both positively-sloped (except Canada and Norway) and flat trend functions. It is true that the 2008 financial crisis is recent history, but "recent history" should not be taken to imply that the episode would only affect the short-run fluctuations of correlations and so correlations would revert to their original, low evolution path after temporary departures. Rather, our empirical strategy reveals that the episode, as a cataclysmic shock rather than a regular volatility shock, has caused significant structural changes in the *long-run* behaviour of 43 correlations.

Thirdly, even though the financial crisis ended in June 2009, 26 markets experienced another upward structural break in their correlation trend functions. There is evidence that investments in commodities have grown rapidly over the last years (especially since 2009) mainly via commodity futures and commodity index funds (see Daskalaki and Skiadopoulos, 2011 and footnote 1 therein). According to Silvennoinen and Thorp (2010) and Tang and Xiong (2010), the surging of index investors in commodities markets would result in strengthening of integration between the commodity futures market and the equity markets. These could be possible explanations for the second upward break in the 26 trend functions.

The trend function of a time series represents its long-run evolution behaviour. If we accept this notion, then the above-discussed evidence is compelling in support of the argument that rising commodity-equity market correlations around the world are a long phenomenon. Our results are contrary to findings of Chong and Miffre (2010) and Büyükşahin et al (2010),[6] but are consistent with those of Silvennoinen and Thorp (2010) and of Tang and Xiong (2010) albeit for individual commodity futures. In particular, Silvennoinen and Thorp (2010) show that "correlations between S&P 500 returns and returns to majority of commodity futures have increased, sometimes sharply and only during the recent crisis, but in many cases, gradually, and from a much earlier date". Our long-run results of commodity future index may be used to infer on theirs that it should also be rises (gradual or sharp) in the secular component or the trend function of correlation that lead to their observed correlation patterns for individual commodity futures. Consolidating our international evidence and their individual commodity evidence, we are able to decisively disapprove the assertion that "despite recent history, commodities still provide portfolio diversification".

3.3 Short-run fluctuation of correlation

Having studied the long-run evolutions of 45 commodity-equity market correlations, we next examine their short-run behaviours. In the short run, conditional correlation as a time series will fluctuate around its long-run trend. Table 6 reports the HILU estimation results of equation (8), which concern whether and how market volatilities cause the short-run fluctuations of the correlations. A negative estimate of $\hat{\delta}_E$, for example, would imply that when the equity market becomes more volatile, its correlation with the commodity futures market tends to fall towards or below the long-run trend. Since investors with equity portfolios need diversification most when

[6] It would be interesting to compare Panel (45) of Figure 1 with Exhibit 9 in Büyükşahin et al (2010), all pertaining to correlations between commodity futures indices and US equity indices. The authors claim no evidence of a secular increase in DCC between 1991 and 2008. We show two clear-cut secular increases in DCC (as represented by two rises in the correlation trend function) in November 2007 and July 2009. Moreover, the authors indicate that the rises in the correlations in fall 2008 were still lower than their peaks in the previous decade, but we uncover that the correlation trend function rose to levels much higher than the peaks.

equity markets are highly volatile, the negative relationship carries the evidence that they could benefit from adding commodity futures to their equity portfolios.

However, as shown in Table 6, the overall picture is rather discouraging. 39 estimates of $\hat{\delta}_E$ on $\sqrt{h_E}$ in equation (8) are positive and significant at the 1% level (except Israel and Japan with the 10% significance level). Thus, conditional correlations between these 39 equity markets and the commodity futures market rise towards or above their long-run trends in periods when the risks of the equity markets increase. This is bad news to index investors holding long positions on the commodity futures index and on these equity indexes: The diversification benefits of commodities even become negative when they are most needed (i.e., when equity market volatilities are high). Moreover, if the short-run results are to be considered in conjunction with the long-run results, the news is clearly even worse, as regular volatility shocks work in the same direction as cataclysmic shocks to raise the correlations and so to weaken the diversification value of commodities.

Note, our results based on decomposition of correlation into long-run and short-run components are in stark contrast to Chong and Miffre's (2010) without such decomposition, although that study looks at individual commodities futures rather than the commodity futures index. Our short-run results of commodity futures index provide stronger evidence than Silvennoinen and Thorp (2010) for individual commodity futures. The two authors report that only half of the investigated commodities have their correlations with the S&P 500 index increased in high stock volatility states.

Four other markets (Egypt, Finland, Malaysia and Morocco) have a significantly negative relationship between correlation deviations (DEV_t) and equity market volatility. So, regular equity volatility shocks drive their correlations to fall, rendering it somewhat worthwhile to add the commodity futures index to portfolios embracing the equity indices from these markets, given the long-run correlation trends. The remaining two markets (Indonesia and Thailand) are neutral in terms of the effect of volatility shocks on their commodity-equity market correlations.

Table 6 also reveals several econometric issues of concern. First, the regression residuals ξ_t are highly persistent, similar to the regression results of equation (6) (See Table 5). This is manifested by the fact that the estimates of the θ_1 coefficient for all the 45 cases are significant at a higher than 1% level, and some of the other θ coefficients' estimates are statistically significant as well. Therefore, if the OLS instead of the HILU regression procedure was employed, results would with little doubt be called into question. Second, the adjusted R-squared is high for all but two cases (Japan and Philippines). This suggests that the explanatory power of the model is high, or that the conditional volatilities $\sqrt{h_E}$ and $\sqrt{h_C}$ are two main drivers of the short-run fluctuations of conditional correlations.

4. Summary and conclusion

The common belief is that one should take a long-term view of the markets and not focus too much on short-term gyrations. Based on this wisdom, some researchers have advised investors to ignore recent upswings in the commodity-equity correlation and continue to invest in commodity futures as an alternative asset class for long-term risk diversification. The wisdom is not wrong, but the advice is. The gut problem with the advice lies in the failure to consider the possibility that recent upswings in the correlations are in fact a long-run phenomenon. Thus, unlike other recent studies such as Silvennoinen and Thorp (2010), Büyükşahin et al (2010) and Chong and Miffre (2010), the present paper contributes by examining this possibility.

To that end, we decompose a DCC-generated correlation series into a secular component (long-run trend) and a cyclical component (short-run fluctuation), and apply the empirical strategy to a broad data set of 45 economies' equity indices. Our main results can be summarised as follows. First, 32 out of the 45 equity markets demonstrate an upward long-run trend in their correlations with the commodity futures market between 2000 and 2010. Second, 43 out of the 45 equity markets have had their correlation trend functions upswing sharply during the recent financial/economic turmoil. Third, conditional correlations of 39 out of the 45 equity markets with the commodity futures market move towards or above their long-run trends when volatilities of these equity markets increase.

In sum, these results constitute compelling international evidence. The evidence, however, portrays a rather disappointing picture to investors: Whether from the long-run or the short-run perspective, the diversification value of the commodity futures index has, in general, vanished. With regard to weakening long-run diversification benefits, two possible explanations could be (a) gradual increases in integration between commodity futures and equity markets; and (b) more and more investors holding both commodity futures and equities in their portfolios via index funds.

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APPENDIX

Table A1 S&P GSCI Components and Dollar Weights

Commodities	Weights
Energy	
Crude Oil	34.6%
Brent Crude	14.3%
Unleaded Gasoline	4.3%
Heating Oil	4.5%
Gas Oil	5.5%
Natural Gas	3.2%
	66.5%
Industrial Metals	
Aluminium	2.4%
Copper	4.0%
Lead	0.5%
Nickel	0.8%
Zinc	0.6%
	8.3%
Precious Metals	
Gold	2.9%
Silver	0.5%
	3.4%
Agriculture	
Wheat	3.8%
Kansas Wheat	0.8%
Corn	4.3%
Soybeans	2.7%
Cotton	1.8%
Sugar	2.8%
Coffee	1.0%
Cocoa	0.3%
	17.4%
Livestock	
Feeder Cattle	0.4%
Live Cattle	2.5%
Lean Hogs	1.4%
	4.3%

Source: S&P GSCI Commodity Indices Fact sheet 2010.

Table A2 MSCI ACWI Index Components and Weights

Developed Markets	# of Securities	Weight
United States	2590	43.12%
Japan	1158	8.64%
Unite Kingdom	393	8.17%
Canada	335	4.70%
France	179	3.45%
Australia	271	3.45%
Germany	174	3.06%
Switzerland	111	2.95%
Sweden	111	1.28%
Spain	73	1.18%
Hong Kong	156	1.12%
Italy	137	1.02%
Netherlands	57	0.96%
Singapore	109	0.70%
Finland	47	0.46%
Denmark	40	0.43%
Norway	58	0.42%
Belgium	51	0.38%
Israel	82	0.32%
Austria	29	0.17%
Greece	40	0.12%
Ireland	22	0.12%
Portugal	24	0.10%
New Zealand	23	0.06%
Total	6270	86.37%
Emerging Markets	# of Securities	Weight
China	454	2.34%
Brazil	151	1.99%
Korea	459	1.89%
Taiwan	565	1.72%
India	372	1.15%
South Africa	115	1.08%
Russia	56	0.79%
Mexico	45	0.58%
Malaysia	128	0.40%
Indonesia	64	0.32%
Thailand	85	0.25%
Turkey	94	0.23%
Chile	35	0.23%
Poland	60	0.22%
Colombia	11	0.10%
Peru	8	0.09%
Philippines	29	0.08%
Egypt	34	0.07%
Czech Republic	7	0.05%
Hungary	7	0.04%
Morocco	6	0.02%
Total	2785	13.63%

Source: MSCI All Country World Investable Market Index Fact Sheet 2010.

Table A3 Summary statistics (Daily returns, %)

Markets	Mean	Max	Min	Std Dev	Skewness	Kurtosis
GSCI	0.0202	7.2159	-9.1695	1.5980	-0.2672	5.2901
Australia	0.0303	8.5091	-16.002	1.5843	-1.0153	13.852
Austria	0.0347	10.261	-10.378	1.4635	-0.3804	11.146
Belgium	-0.0008	10.718	-12.490	1.5431	-0.217	9.8835
Brazil	0.0515	16.857	-17.963	2.5030	-0.2744	8.3986
Canada	0.0285	10.381	-14.446	1.5926	-0.809	12.441
Chile	0.0558	14.551	-11.670	1.3494	-0.2772	13.340
China	0.0314	9.5280	-9.7067	1.7150	0.0253	7.3699
Colombia	0.0802	12.675	-11.778	2.0962	-0.1164	16.376
Czech	0.0644	19.720	-16.747	1.8943	-0.1839	14.612
Denmark	0.0350	10.689	-13.858	1.5100	-0.3077	10.435
Egypt	0.0398	8.9845	-19.913	1.7495	-0.7231	13.774
Finland	-0.0277	16.480	-20.288	2.4824	-0.2383	8.0832
France	-0.0055	12.143	-11.737	1.6840	0.0626	9.4999
Germany	0.0099	12.370	-9.601	1.7301	-0.0049	7.7969
Greece	-0.0455	13.070	-11.100	1.9550	-0.0919	7.5937
Hong Kong	0.0136	10.590	-11.586	1.4999	-0.2503	9.5149
Hungary	0.0291	20.250	-20.61	2.2797	-0.0214	12.559
India	0.0482	18.107	-12.818	1.8440	-0.3803	10.120
Indonesia	0.0479	15.042	-19.950	2.1501	-0.4484	9.8177
Ireland	-0.0425	13.599	-18.931	1.9359	-0.7299	12.986
Israel	0.0204	8.2848	-9.7934	1.5085	-0.3301	7.5161
Italy	-0.0159	12.381	-10.864	1.6341	0.0194	10.331
Japan	-0.0134	11.644	-11.186	1.6032	-0.1738	7.0220
Korea	0.0231	24.655	-20.346	2.1939	-0.2901	14.325
Malaysia	0.0339	5.5410	-10.930	1.0805	-0.6165	10.629
Mexico	0.0496	15.206	-10.684	1.7735	-0.0007	9.1658
Morocco	0.0257	6.2507	-7.6987	1.0885	-0.1615	7.5851
Netherlands	-0.0121	12.316	-11.857	1.7149	-0.0657	9.9718
New Zealand	0.0074	9.3181	-9.2549	1.3798	-0.5377	7.6353
Norway	0.0336	15.604	-14.262	2.0187	-0.4315	10.696
Peru	0.0708	13.250	-15.988	2.0697	-0.4938	10.389
Philippines	0.0093	21.972	-14.494	1.6709	0.8214	20.543
Poland	0.0232	14.234	-13.378	2.1011	-0.1455	6.9796
Portugal	-0.0080	11.525	-13.293	1.4019	-0.0226	12.518
Russia	0.0600	23.661	-23.324	2.6633	-0.1370	11.590
Singapore	0.0128	8.5634	-9.809	1.4529	-0.2387	7.5940
South Africa	0.0444	12.889	-12.852	1.8271	-0.2997	8.8286
Spain	0.0044	14.968	-10.657	1.6741	0.0983	10.398
Sweden	0.0095	14.391	-10.564	2.0763	0.1167	7.0167
Switzerland	0.0132	10.016	-7.5074	1.3207	0.0562	8.4308
Taiwan	0.0046	8.2571	-10.571	1.6527	-0.1663	5.5996
Thailand	0.0352	10.674	-18.240	1.8074	-0.6226	10.750
Turkey	0.0107	22.015	-27.420	3.1715	-0.1702	10.267
UK	-0.0066	12.219	-10.538	1.4937	-0.0691	11.716
US	-0.0054	10.957	-9.4695	1.3537	-0.1144	10.899

Table A4 GARCH parameter estimates

	Australia	Austria	Belgium	Brazil	Canada	Chile	China	Colombia	Czech
ω	0.0313^{***}	0.0222^{***}	0.0263^{***}	0.1002^{***}	0.0224^{***}	0.0345^{***}	0.0235^{***}	0.1233	0.0419^{***}
α	0.0773^{***}	0.0707^{***}	0.1004^{***}	0.0231^{***}	0.0513^{***}	0.1001^{***}	0.0609^{***}	0.0334	0.1023^{***}
β	0.8811^{***}	0.9055^{***}	0.8682^{***}	0.8766^{***}	0.9262^{***}	0.8584^{***}	0.9150^{***}	0.8423	0.8513^{***}

	Denmark	Egypt	Finland	France	Germany	Greece	Hong Kong	Hungary	India
ω	0.0320^{***}	0.0213^{***}	0.0106^{***}	0.0234^{***}	0.0249^{***}	0.0257^{***}	0.0124^{***}	0.0765^{***}	0.0306^{***}
α	0.0641^{***}	0.0349^{***}	0.0299^{***}	0.0834^{***}	0.0729^{***}	0.0656^{***}	0.0562^{***}	0.0420^{***}	0.1474^{***}
β	0.9040^{***}	0.9361^{***}	0.9586^{***}	0.8893^{***}	0.8996^{***}	0.9084^{***}	0.9286^{***}	0.8811^{***}	0.8183^{***}

	Indonesia	Ireland	Israel	Italy	Japan	Korea	Malaysia	Mexico	Morocco
ω	0.0285^{***}	0.0438^{***}	0.0167^{***}	0.0210^{***}	0.0251^{***}	0.0352^{***}	0.0116^{*}	0.0339^{***}	0.0523^{***}
α	0.0547^{***}	0.0675^{***}	0.0479^{***}	0.0945^{***}	0.0720^{***}	0.0396^{***}	0.0795	0.0586^{***}	0.1003^{***}
β	0.8952^{***}	0.8810^{***}	0.9339^{***}	0.8794^{***}	0.9003^{***}	0.9235^{***}	0.9046^{***}	0.9031^{***}	0.8464^{***}

	Netherlands	New Zealand	Norway	Peru	Philippines	Poland	Portugal	Russia	Singapore
ω	0.0116^{***}	0.0250^{***}	0.0500^{***}	0.0266^{***}	0.1161	0.0298^{***}	0.0222^{***}	0.1227^{***}	0.0200^{***}
α	0.1018^{***}	0.0622^{***}	0.0780^{***}	0.0575^{***}	0.0469^{*}	0.0501^{***}	0.0715^{***}	0.0526^{***}	0.0851^{***}
β	0.8774^{***}	0.9126^{***}	0.8660^{***}	0.9139^{***}	0.8315^{***}	0.9115^{***}	0.9059^{***}	0.8153^{***}	0.8939^{***}

	Spain	South Africa	Sweden	Switzerland	Taiwan	Thailand	Turkey	UK	US
ω	0.0214^{***}	0.0554^{***}	0.0166^{***}	0.0268^{***}	0.0119^{***}	0.1040	0.1107^{***}	0.0176^{***}	0.0108^{***}
α	0.0754^{***}	0.0768^{***}	0.0550^{***}	0.0919^{***}	0.0546^{***}	0.1643	0.0436^{***}	0.1022^{***}	0.0629^{***}
β	0.9028^{***}	0.8609^{***}	0.9192^{***}	0.8723^{***}	0.9280^{***}	0.7320	0.8453^{***}	0.8801^{***}	0.9201^{***}

	GSCI
ω	0.0347^{***}
α	0.0244^{***}
β	0.9401^{***}

Note. The *t*-values are calculated using robust standard errors adjusted for two step estimation biases. *** denote significance at the 1% level.* denote significance at the 10% level.

Table A5 DCC parameter estimates

	Australia	Austria	Belgium	Brazil	Canada	Chile	China	Colombia	Czech
a	0.0077^{***}	0.0161^{***}	0.0234^{***}	0.0101^{***}	0.0097^{***}	0.0237^{***}	0.0199^{***}	0.0053^{***}	0.0144^{***}
b	0.9739^{***}	0.9578^{***}	0.9464^{***}	0.9870^{***}	0.9896^{***}	0.9492^{***}	0.7976^{***}	0.9758^{***}	0.9578^{***}

	Denmark	Egypt	Finland	France	Germany	Greece	Hong Kong	Hungary	India
a	0.0169^{***}	0.0033^{***}	0.0166^{***}	0.0298^{***}	0.0258^{***}	0.0177^{***}	0.0023^{***}	0.0135^{***}	0.0109^{***}
b	0.9470^{***}	0.7107^{***}	0.9557^{***}	0.9440^{***}	0.9516^{***}	0.9374^{***}	0.9872^{***}	0.9631^{***}	0.9668^{***}

	Indonesia	Ireland	Israel	Italy	Japan	Korea	Malaysia	Mexico	Morocco
a	0.0007^{***}	0.0113^{***}	0.0101^{***}	0.0249^{***}	0.0322^{***}	0.0048^{***}	0.0017^{***}	0.0188^{***}	0.0069^{***}
b	0.9795^{***}	0.9510^{***}	0.9494^{***}	0.9464^{***}	0.1956	0.9865^{***}	0.9834^{***}	0.9680^{***}	0.9608^{***}

	Netherlands	New Zealand	Norway	Peru	Philippines	Poland	Portugal	Russia	Singapore
a	0.0276^{***}	0.0044^{***}	0.0078^{***}	0.0104^{***}	0.0078^{***}	0.0074^{***}	0.0244^{***}	0.0084^{***}	0.0012^{***}
b	0.9534^{***}	0.9808^{***}	0.9919^{***}	0.9873^{***}	0.5071^{***}	0.9840^{***}	0.9437^{***}	0.9764^{***}	0.9825^{***}

	Spain	South Africa	Sweden	Switzerland	Taiwan	Thailand	Turkey	UK	US
a	0.0263^{***}	0.0296^{***}	0.0168^{***}	0.0274^{***}	0.0012^{***}	0.0072^{***}	0.0122^{***}	0.0343^{***}	0.0169^{***}
b	0.9535^{***}	0.9182^{***}	0.9497^{***}	0.9363^{***}	0.9804^{***}	0.9720^{***}	0.9723^{***}	0.9354^{***}	0.9739^{***}

Note. The *t*-values are calculated using robust standard errors adjusted for two step estimation biases. *** denote significance at the 1% level.

Table 1 Simple correlations between GSCI and equity indices from developed markets

Markets	2000-2010		2000-2007		2008-2010	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
Australia	0.268***	14.87	0.111***	5.056	0.407***	12.62
Austria	0.296***	16.57	0.077***	3.519	0.476***	15.32
Belgium	0.240***	13.26	0.027	1.211	0.447***	14.14
Canada	0.399***	23.30	0.182***	8.402	0.614***	22.03
Denmark	0.287***	16.06	0.079***	3.586	0.495***	16.13
Finland	0.192***	10.48	0.045**	2.049	0.461***	14.71
France	0.290***	16.22	0.061***	2.797	0.533***	17.85
Hong Kong	0.152***	8.238	0.034	1.527	0.290***	8.584
Greece	0.223***	12.26	0.041*	1.866	0.392***	12.07
Germany	0.248***	13.72	0.025	1.135	0.525***	17.49
Ireland	0.235***	12.94	0.073***	3.326	0.369***	11.23
Italy	0.299***	16.80	0.055**	2.485	0.533***	17.84
Israel	0.103***	5.529	0.011	0.506	0.305***	9.055
Japan	0.109***	5.845	0.088***	3.994	0.137***	3.924
Netherlands	0.278***	15.51	0.031	1.395	0.549***	18.60
New Zealand	0.216***	11.84	0.058***	2.647	0.399***	12.34
Norway	0.392***	22.83	0.159***	7.291	0.595***	20.94
Portugal	0.268***	14.92	0.048**	2.176	0.487***	15.79
Singapore	0.185***	10.05	0.050**	2.263	0.344***	10.38
Spain	0.272***	15.15	0.044**	2.013	0.499***	16.30
Sweden	0.265***	14.70	0.065***	2.961	0.486***	15.76
Switzerland	0.244***	13.47	0.039**	1.774	0.489***	15.89
UK	0.320***	18.10	0.074***	3.350	0.563***	19.29
US	0.202***	11.02	-0.011	-0.495	0.427***	13.39

Table 2 Simple correlations between GSCI and equity indices from emerging markets

Markets	2000-2010		2000-2007		2008-2010	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
Brazil	0.264***	14.67	0.048**	2.188	0.554***	18.84
Chile	0.212***	11.63	0.033	1.506	0.419***	13.08
China	0.084***	4.493	-0.001	-0.035	0.179***	5.140
Colombia	0.174***	9.461	0.057***	2.612	0.444***	14.04
Czech	0.275***	15.31	0.080***	3.666	0.482***	15.56
Egypt	0.081***	4.341	0.001	0.439	0.168***	4.837
Hungary	0.279***	15.55	0.108***	4.954	0.435***	13.67
Indonesia	0.133***	7.179	0.072***	3.277	0.226***	6.559
India	0.167***	9.076	0.021	0.970	0.353***	10.67
Korea	0.137***	7.408	0.046**	2.111	0.258***	7.557
Malaysia	0.133***	7.165	0.053**	2.389	0.248***	7.257
Mexico	0.259***	14.37	0.065***	2.976	0.500***	16.35
Morocco	0.094***	5.042	-0.008	-0.356	0.229***	6.668
Peru	0.288***	16.13	0.130***	5.973	0.468***	14.98
Philippines	0.100***	5.406	0.060***	2.731	0.163***	4.686
Poland	0.289***	16.14	0.092***	4.209	0.503***	16.46
Russia	0.223***	12.27	0.068***	3.107	0.419***	13.07
South Africa	0.320***	18.08	0.139***	6.374	0.507***	16.65
Taiwan	0.106***	5.733	0.026	1.171	0.242***	7.050
Thailand	0.145***	7.866	0.066***	2.980	0.272***	8.009
Turkey	0.164***	8.927	0.050**	2.251	0.422***	13.17

Table 3 Log likelihood ratio tests for structural break in unconditional correlation

	H_0: no break H_1: 1 break	p-value	H_0: no break H_1: 2 breaks	p-value	H_0: 1 break H_1: 2 breaks	p-value	Break
Australia	4.210**	0.0402	10.96***	0.0042	6.748**	0.0343	2
Austria	3.814*	0.0508	8.140**	0.0171	4.326**	0.0375	2
Belgium	10.58***	0.0011	14.89***	0.0006	4.309**	0.0379	2
Brazil	18.79***	0.0000	21.00***	0.0000	2.212	0.1369	1
Canada	2.550	0.1103	3.653	0.1610	1.102	0.2938	0
Chile	13.41***	0.0003	16.66***	0.0002	3.245*	0.0716	2
China	8.968***	0.0027	18.09***	0.0001	9.119***	0.0025	2
Colombia	21.89***	0.0000	22.26***	0.0000	0.373	0.5412	1
Czech	5.161**	0.0231	6.076**	0.0479	0.915	0.3388	1
Denmark	8.966***	0.0028	16.27***	0.0003	7.301***	0.0069	2
Egypt	7.133***	0.0076	8.023**	0.0181	0.890	0.3455	1
Finland	14.69***	0.0001	19.47***	0.0001	4.779**	0.0288	2
France	11.01***	0.0009	14.00***	0.0009	2.983*	0.0841	2
Germany	10.06***	0.0015	14.23***	0.0008	4.170**	0.0412	2
Greece	8.843***	0.0029	-	-	-	-	1
Hong Kong	11.47***	0.0007	13.73***	0.0010	2.261	0.1327	1
Hungary	4.542**	0.0331	6.510**	0.0386	1.967	0.1607	1
India	3.609*	0.0575	7.871**	0.0195	4.263**	0.0390	2
Indonesia	3.014*	0.0826	5.732*	0.0569	2.718*	0.0992	2
Ireland	6.305**	0.0120	13.52***	0.0012	7.218***	0.0072	2
Israel	8.046***	0.0046	-	-	-	-	1
Italy	11.22***	0.0008	14.42***	0.0007	3.195*	0.0739	2
Japan	3.732*	0.0534	4.828*	0.0895	1.095	0.2953	1
Korea	2.515	0.1128	5.914*	0.0520	3.399*	0.0652	2
Malaysia	7.271***	0.0070	10.16***	0.0062	2.887*	0.0893	2
Mexico	6.948***	0.0084	14.10***	0.0009	7.151***	0.0075	2
Morocco	7.447***	0.0064	-	-	-	-	1
Netherlands	29.15***	0.0000	30.44***	0.0000	1.292	0.2556	1
New Zealand	13.33***	0.0002	20.83***	0.0000	7.495***	0.0062	2
Norway	1.529	0.2163	1.595	0.4506	0.066	0.7973	0
Peru	3.664*	0.0556	3.998	0.1355	0.334	0.5634	1
Philippines	4.419**	0.0355	4.431	0.1091	0.012	0.9126	1
Poland	6.120**	0.0134	7.986**	0.0184	1.866	0.1719	1
Portugal	11.07***	0.0009	14.39***	0.0008	3.314*	0.0687	2
Russia	25.27***	0.0000	29.28***	0.0000	4.013**	0.0452	2
Singapore	10.78***	0.0010	14.79***	0.0006	4.010**	0.0453	2
South Africa	13.28***	0.0003	20.76***	0.0000	7.487***	0.0062	2
Spain	10.66***	0.0011	-	-	-	-	1
Sweden	13.18***	0.0003	21.38***	0.0000	8.208***	0.0042	2
Switzerland	11.36***	0.0007	21.74***	0.0000	10.38***	0.0013	2
Taiwan	5.953**	0.0147	9.232***	0.0099	3.279*	0.0702	2
Thailand	3.310*	0.0689	-	-	-	-	1
Turkey	9.285***	0.0023	10.11***	0.0064	0.820	0.3653	1
UK	13.67***	0.0002	16.88***	0.0002	3.211*	0.0731	2
US	8.801***	0.0030	13.77***	0.0010	4.965**	0.0259	2

Note. Columns 2, 4 and 6 present log-likelihood test statistics corresponding to the null and alternative hypotheses given in the first row. Columns 3, 5 and 7 present the corresponding p-values. Column 8 presents the number of break based on statistical inference. "1" means that the equity market's correlation with the commodity futures market has the first structural break (at December 1, 2007) only.

Table 4 Tests for trend stationarity of conditional correlation

Market	Break	Time trend	ϕ_2	*t*-statistic	1.0%	5.0%	10%
Australia	2	Yes	-0.023***	-7.155	-4.614	-4.040	-3.742
Austria	2	Yes	-0.039***	-8.276	-4.195	-3.351	-2.835
Belgium	2	Yes	-0.037***	-7.584	-4.896	-4.320	-4.006
Brazil	1	Yes	-0.008**	-4.244	-4.286	-3.782	-3.470
Canada	0	Yes	-0.007**	-3.587	-3.876	-3.367	-3.100
Chile	2	No	-0.029***	-7.144	-2.030	-1.514	-1.170
China	2	No	-0.177***	-18.60	-1.422	-0.983	-0.768
Colombia	1	No	-0.010***	-6.551	-2.327	-1.680	-1.333
Czech	1	Yes	-0.037***	-8.410	-4.284	-3.758	-3.465
Denmark	2	Yes	-0.044***	-8.178	-4.985	-4.348	-4.020
Egypt	1	No	-0.281***	-27.10	-2.210	-1.661	-1.268
Finland	2	Yes	-0.032***	-7.741	-4.774	-4.163	-3.844
France	2	Yes	-0.034***	-7.166	-4.929	-4.245	-3.918
Germany	2	Yes	-0.028***	-6.624	-4.750	-4.197	-3.888
Greece	1	Yes	-0.054***	-9.242	-4.921	-4.325	-3.912
Hong Kong	1	Yes	-0.012***	-8.360	-4.105	-3.646	-3.331
Hungary	1	Yes	-0.030***	-7.360	-4.543	-3.948	-3.679
India	2	Yes	-0.029***	-7.060	-5.092	-4.399	-4.095
Indonesia	2	Yes	-0.021***	-18.91	-3.943	-3.114	-2.730
Ireland	2	Yes	-0.042***	-8.831	-3.890	-2.938	-2.300
Israel	1	No	-0.040***	-8.179	-2.010	-1.413	-1.088
Italy	2	Yes	-0.037***	-8.069	-4.977	-4.376	-4.075
Japan	1	No	-0.763***	-43.24	-0.333	-0.249	-0.201
Korea	2	Yes	-0.012***	-5.355	-4.496	-3.958	-3.667
Malaysia	2	No	-0.013***	-8.665	-2.660	-2.014	-1.659
Mexico	2	No	-0.014***	-4.673	-2.225	-1.518	-1.178
Morocco	1	No	-0.032***	-7.011	-2.285	-1.532	-1.143
Netherlands	1	Yes	-0.027***	-6.540	-4.422	-3.798	-3.561
New Zealand	2	No	-0.010***	-4.457	-2.345	-1.664	-1.333
Norway	0	Yes	-0.007***	-4.177	-4.117	-3.514	-3.178
Peru	1	Yes	-0.012***	-4.642	-4.468	-3.889	-3.540
Philippines	1	No	-0.490***	-21.10	-0.774	-0.537	-0.404
Poland	1	Yes	-0.013***	-6.092	-4.250	-3.691	-3.439
Portugal	2	Yes	-0.037***	-7.498	-4.807	-4.198	-3.878
Russia	2	Yes	-0.020***	-6.549	-4.421	-3.973	-3.675
Singapore	2	Yes	-0.018***	-17.81	-3.926	-3.340	-3.046
South Africa	2	Yes	-0.063***	-10.46	-5.309	-4.706	-4.346
Spain	1	Yes	-0.025***	-5.455	-4.688	-4.028	-3.734
Sweden	2	Yes	-0.039***	-8.612	-4.657	-4.137	-3.830
Switzerland	2	Yes	-0.043***	-9.132	-5.086	-4.472	-4.117
Taiwan	2	No	-0.018***	-13.07	-3.225	-2.537	-2.182
Thailand	1	Yes	-0.020***	-6.483	-4.132	-3.477	-3.147
Turkey	1	Yes	-0.018***	-5.426	-4.673	-3.995	-3.654
UK	2	Yes	-0.039***	-8.252	-5.161	-4.529	-4.192
US	2	No	-0.009***	-3.190	-2.014	-1.394	-1.057

Note. Percentage points in the last three columns are based on 2,000 replications, and are used as the critical values of the t-statistics for the estimated ϕ_2. ** indicates significant at the 5% level. *** indicates significant at the 1% level.

Table 5 Regressions to estimate the trend function

	μ	c_0 ($\times 10^{-4}$)	c_1	c_2	d_1	d_2	d_3	d_4	d_5
	Equation (6): $\rho_t = \mu + c_0 T + c_1 D_{1,t} + c_2 D_{2,t} + \sum_{k=1}^{m} d_k \rho_{t-k} + e_t, \quad m \le 5$								
Australia	0.183***	0.795**	0.368***	0.334***	0.978***	-	-	-	-
Austria	-0.023	2.973***	0.898**	0.564***	0.944***	-0.002	0.051**	-0.033*	-
Belgium	-0.101	2.691***	0.687***	0.713***	0.960***	-0.036	0.039**	-	-
Brazil	-0.043	0.793**	0.290***	-	0.992***	-	-	-	-
Canada	-0.025	1.816***	-	-	0.993***	-	-	-	-
Chile	0.097*	-	0.745***	0.484***	0.971***	-	-	-	-
China	-0.065	-	2.424***	3.406***	0.823***	-	-	-	-
Colombia	0.052***	-	0.362***	-	0.990***	-	-	-	-
Czech	0.138**	1.843***	1.011***	-	0.963***	-	-	-	-
Denmark	0.161**	1.983***	1.075***	0.665***	0.935***	-0.005	0.060**	-0.035*	-
Egypt	0.166***	-	4.859***	-	0.719***	-	-	-	-
Finland	0.107	1.336**	0.742***	0.468***	0.968***	-	-	-	-
France	0.053	2.429**	0.659***	0.669***	0.967***	-0.034	0.034*	-	-
Germany	-0.064	1.950**	0.712***	0.526***	0.987***	-0.049	0.034*	-	-
Greece	0.109	2.121***	1.239***	-	0.951***	-0.042*	0.037*	-	-
Hong Kong	0.033***	0.241***	0.268***	-	0.988***	-	-	-	-
Hungary	0.178***	1.416***	0.623***	-	0.969***	-	-	-	-
India	-0.068	1.333***	0.537***	0.420***	0.971***	-	-	-	-
Indonesia	0.163***	0.079***	0.245***	0.168***	0.945***	0.002	0.032*	-	-
Ireland	0.217***	0.974**	0.649***	0.804***	0.966***	-0.040*	0.033*	-	-
Israel	0.058***	-	1.109***	-	0.960***	-	-	-	-
Italy	0.055	2.340***	0.832***	0.701***	0.963***	-	-	-	-
Japan	6.287***	-	4.883***	-	0.237***	-	-	-	-
Korea	0.030	0.531***	0.078**	0.126***	0.988***	-	-	-	-
Malaysia	0.074***	-	0.180***	0.189***	0.960***	-0.009	0.081**	-0.010	-0.035**
Mexico	0.096**	-	0.338***	0.472***	0.992***	-0.042	0.055**	-0.050**	0.031*
Morocco	0.021	-	0.624***	-	0.964***	-0.043	0.045*	0.035	-0.033*
Netherlands	-0.086	2.561***	0.802***	-	0.968***	-0.029	0.033*	-	-
Norway	-0.047*	1.720***	-	-	0.997***	-0.042	0.038**	-	-
New Zealand	0.117***	-	0.474***	0.217***	0.965***	0.014	-0.032	0.036**	-
Peru	-0.033	2.324***	0.154**	-	0.994***	-0.047	0.041**	-	-
Philippines	2.592***	-	5.189***	-	0.516***	0.015	-0.007	0.029	-0.043**
Poland	0.043	0.720**	0.390***	-	0.987***	-	-	-	-
Portugal	0.076	1.493*	1.037***	0.438**	0.960***	-0.033	0.035*	-	-
Russia	0.079*	0.938***	0.488***	0.324***	0.980***	-	-	-	-
Singapore	0.107***	0.125***	0.351**	0.276**	0.945***	0.038**	-	-	-
South Africa	0.534***	3.157***	1.192***	1.011***	0.937***	-	-	-	-
Spain	-0.016	1.990**	0.658***	-	0.961***	-0.029	0.042**	-	-
Sweden	0.183**	1.159*	0.982***	0.785***	0.961***	-	-	-	-
Switzerland	0.011	2.555***	0.864***	1.063***	0.957***	-	-	-	-
Taiwan	0.064***	-	0.321***	0.143***	1.007***	-0.045	0.063**	-0.043**	-
Thailand	0.100***	0.402**	0.356***	-	0.964***	-0.011	0.062***	-0.035**	-
Turkey	0.000	0.858*	0.446***	-	0.977***	-0.054*	0.058***	-	-
UK	0.067	2.926***	0.807**	0.787***	0.961***	-	-	-	-
US	-0.012	-	0.323**	0.359***	0.972***	-0.016	0.035*	-	-

*Note. The time-varying correlation coefficient ρ_t is expressed as percentages within the range [-100%, 100%]. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level.*

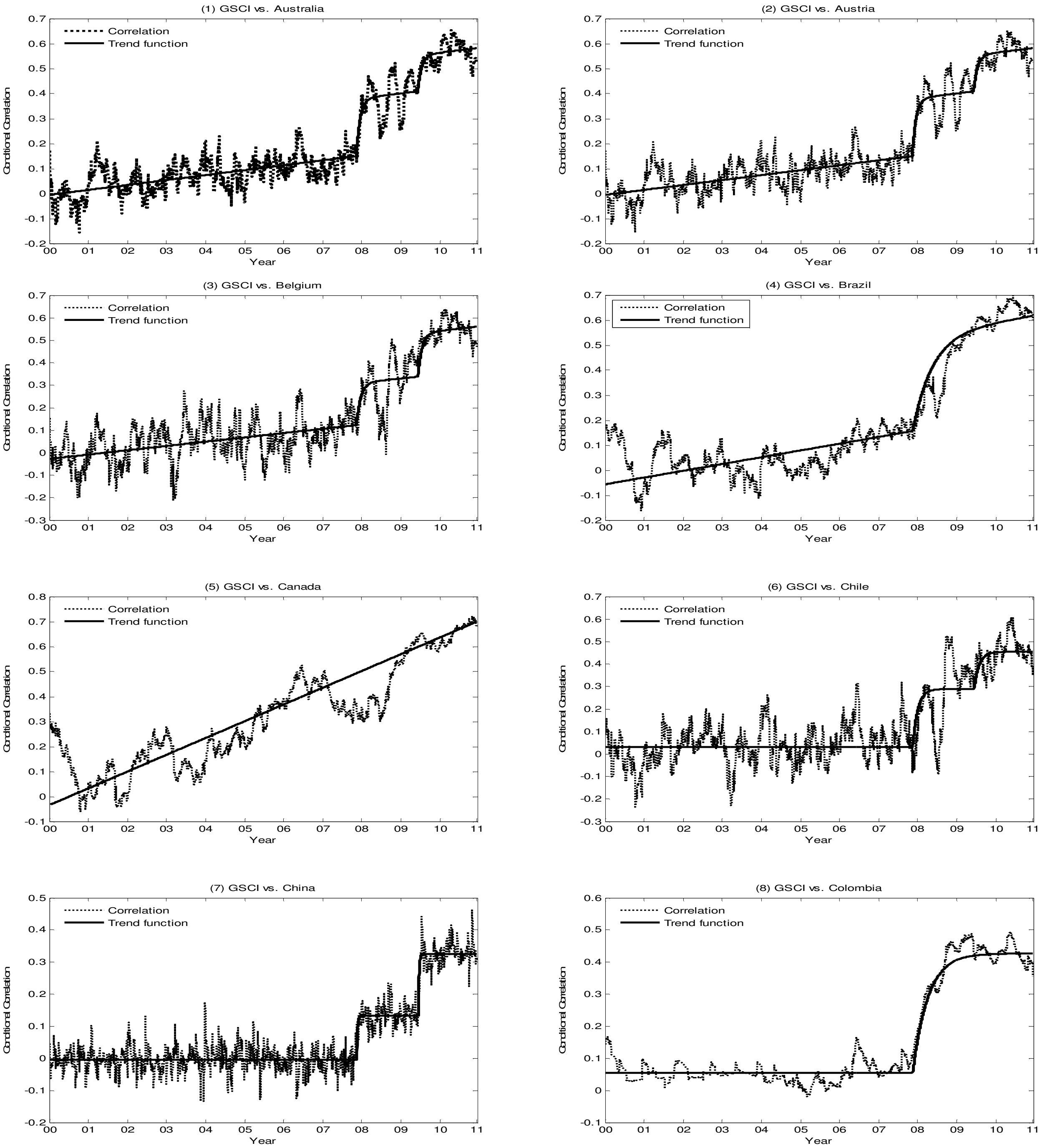
Table 6 Regressions to investigate short-run fluctuations

Equation (8) : $DEV_t = \delta_0 + \delta_E \sqrt{h_{E,t}} + \delta_C \sqrt{h_{C,t}} + \xi_t, \quad \xi_t = z_t + \sum_{i=1}^{q} \theta_i \xi_{t-i}, \; q \leq 5$

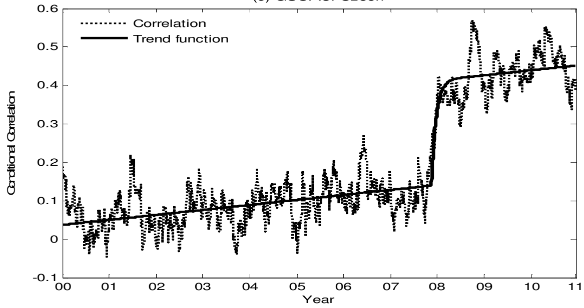
	δ_0	δ_E	δ_C	θ_1	θ_2	θ_3	θ_4	θ_5	$\bar{R}^2$
Australia	-3.182***	0.708***	1.345***	0.978***	-	-	-	-	0.96
Austria	-4.706***	2.988***	0.361	0.961***	-	-	-	-	0.93
Belgium	-2.491	1.959***	-0.208	0.963***	-0.036	0.037**	-	-	0.93
Brazil	-3.964**	0.532***	1.072***	0.991***	-	-	-	-	0.98
Canada	-7.560***	1.558***	1.070***	0.993***	-	-	-	-	0.99
Chile	-2.881	2.784***	-0.329	0.969***	-	-	-	-	0.94
China	-1.951***	0.593**	0.644	0.824***	-	-	-	-	0.67
Colombia	-2.832***	0.460***	1.294***	0.989***	-	-	-	-	0.98
Czech	-5.011***	1.286***	1.778***	0.960***	-	-	-	-	0.93
Denmark	-5.261***	3.343***	0.420	0.927***	-0.003	0.064**	-0.035*	-	0.92
Egypt	-0.118	-0.201***	0.298***	0.732***	-	-	-	-	0.54
Finland	-2.106	-0.727**	2.368***	0.970***	-	-	-	-	0.94
France	-6.243***	3.055***	0.945	0.971***	-0.040	0.034*	-	-	0.93
Germany	-3.364*	2.401***	-0.357	0.984***	-0.045*	0.031*	-	-	0.94
Greece	-2.880***	1.459***	0.158	0.951***	-0.043*	0.038**	-	-	0.89
Hong Kong	-0.595**	0.220***	0.134*	0.998***	-0.042	0.057**	-0.030*	-	0.98
Hungary	-3.611***	1.139***	0.756*	0.961***	-0.025	0.033*	-	-	0.94
India	-2.816***	0.492***	1.198***	0.971***	-	-	-	-	0.95
Indonesia	-0.207***	-0.011	0.138***	0.947***	0.002	0.031*	-	-	0.98
Ireland	-3.216***	1.151***	0.781**	0.969***	-0.045*	0.036*	-	-	0.92
Israel	-1.063	0.512*	0.220	0.962***	-	-	-	-	0.93
Italy	-3.628***	2.300***	0.099	0.960***	-	-	-	-	0.93
Japan	-0.195	0.320*	-0.189	0.236***	-	-	-	-	0.06
Korea	-1.966***	0.360***	0.589***	0.987***	-	-	-	-	0.98
Malaysia	-0.181	-0.202***	0.254***	0.955***	-0.009	0.080***	-0.001	-0.042**	0.98
Mexico	-1.258	1.493***	-0.682	0.993***	-0.047*	0.060**	-0.054**	0.032*	0.97
Morocco	0.067	-0.491***	0.274	0.967***	-0.047*	0.052***	-	-	0.94
Netherlands	-4.979***	2.092***	1.021	0.970***	-0.030	0.032*	-	-	0.94
New Zealand	-2.092***	0.785***	0.699***	0.975***	0.007	-0.034	0.037**	-	0.97
Norway	-7.464***	1.035***	1.464***	0.998***	-0.040	0.035*	-	-	0.99
Peru	-8.260***	2.312***	1.762***	0.995***	-0.046*	0.039**	-	-	0.98
Philippines	-0.352***	0.184***	0.039	0.515***	0.011	-0.009	0.027	-0.042**	0.28
Poland	-4.982***	1.161***	1.547***	0.985***	-	-	-	-	0.98
Portugal	-6.973***	2.347***	2.540***	0.961***	-0.033	0.035*	-	-	0.93
Russia	-3.352***	0.337***	1.548***	0.979***	-	-	-	-	0.96
Singapore	-0.284**	0.151***	0.037	0.946***	0.036*	-	-	-	0.99
South Africa	-9.851***	3.462***	2.651***	0.940***	-	-	-	-	0.88
Spain	-3.700**	2.967***	-0.661	0.964***	-0.032	0.041**	-	-	0.95
Sweden	-5.817***	1.962***	1.332**	0.960***	-	-	-	-	0.93
Switzerland	-7.075***	3.597***	1.715**	0.957***	-	-	-	-	0.92
Taiwan	-0.264**	0.107***	0.067*	1.010***	-0.053**	0.070***	-0.045**	-	0.98
Thailand	-1.518***	-0.012	0.959***	0.969***	-0.016	0.065**	-0.042**	-	0.96
Turkey	-3.405***	0.334***	1.428***	0.978***	-0.055**	0.058***	-		0.96
UK	-8.197***	3.988***	1.839*	0.960***	-	-	-	-	0.93
US	-0.062	3.823***	-2.748***	0.988***	-	-	-	-	0.98

Note. * *indicates significance at the 10% level.* ** *indicates significance at the 5% level.* *** *indicates significance at the 1% level*

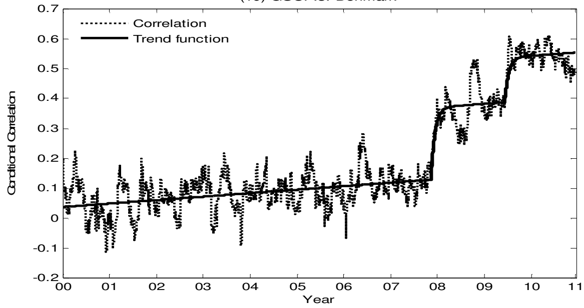
Figure 1 Plots of conditional correlations and their trend functions



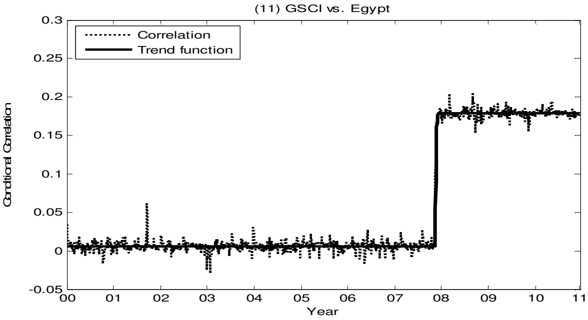
(9) GSCI vs. Czech



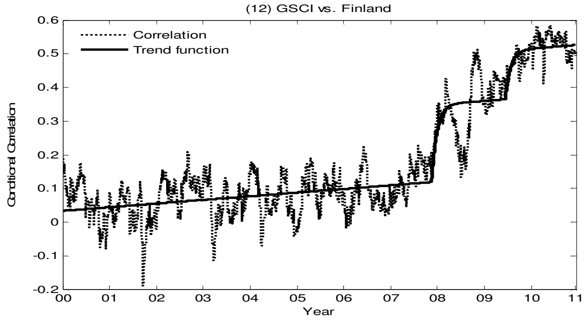
(10) GSCI vs. Denmark



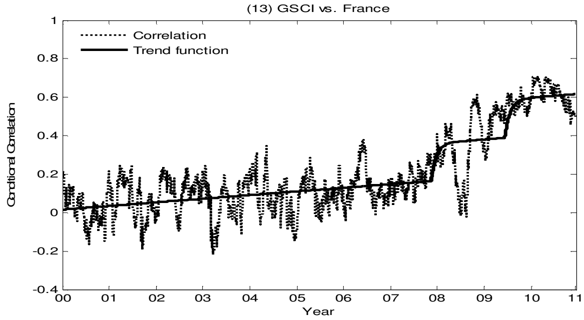
(11) GSCI vs. Egypt



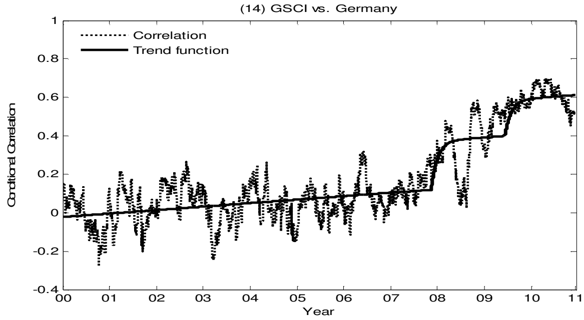
(12) GSCI vs. Finland



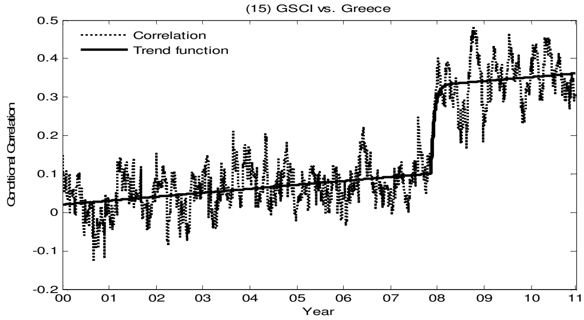
(13) GSCI vs. France



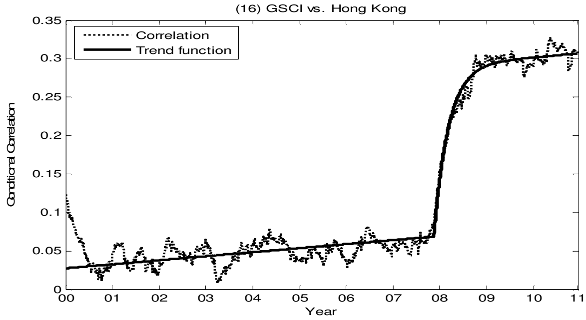
(14) GSCI vs. Germany



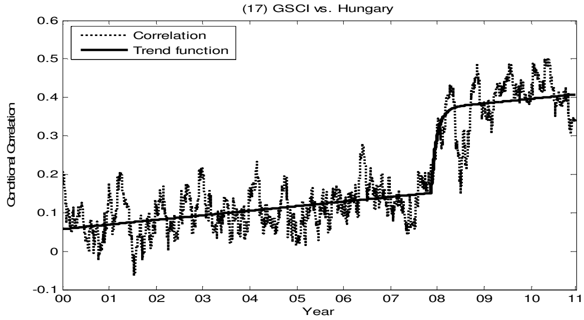
(15) GSCI vs. Greece



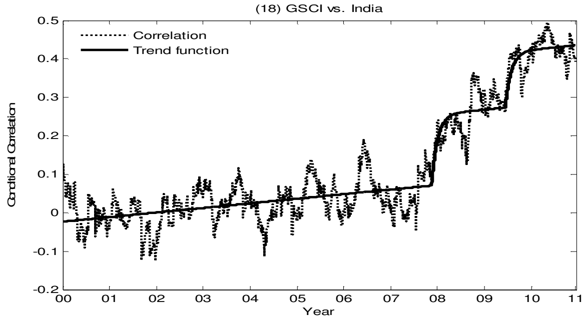
(16) GSCI vs. Hong Kong

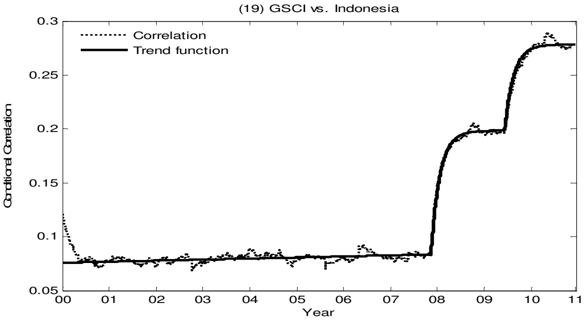


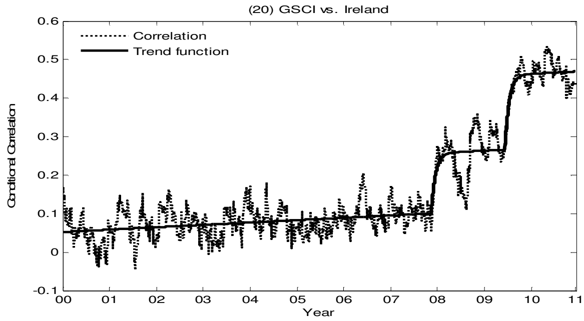
(17) GSCI vs. Hungary

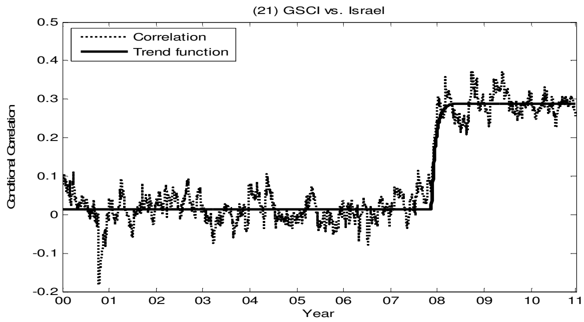


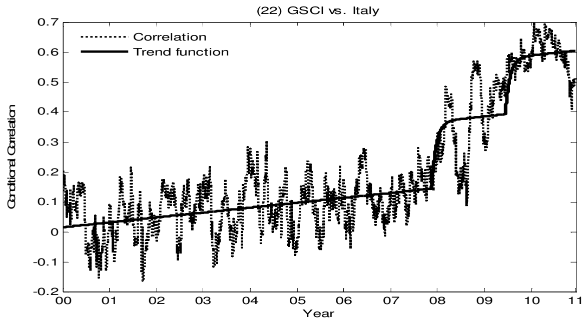
(18) GSCI vs. India

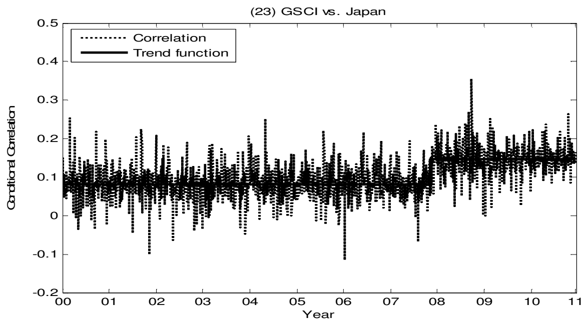


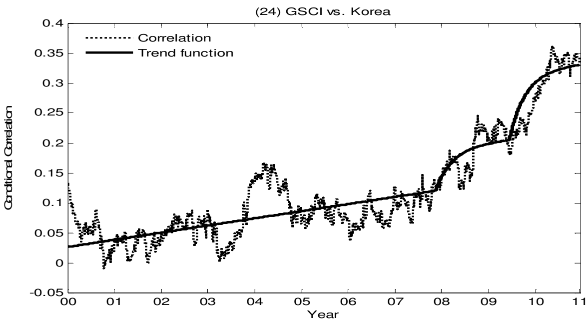

(19) GSCI vs. Indonesia
Correlation
Trend function
Conditional Correlation
Year

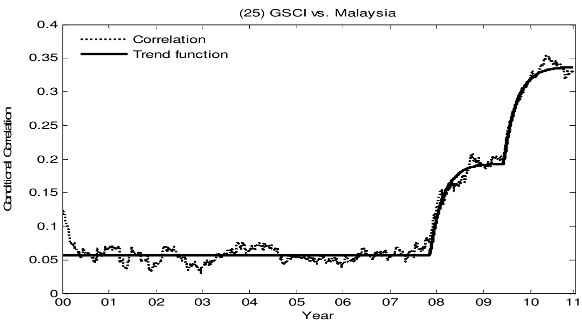

(20) GSCI vs. Ireland
Correlation
Trend function
Conditional Correlation
Year

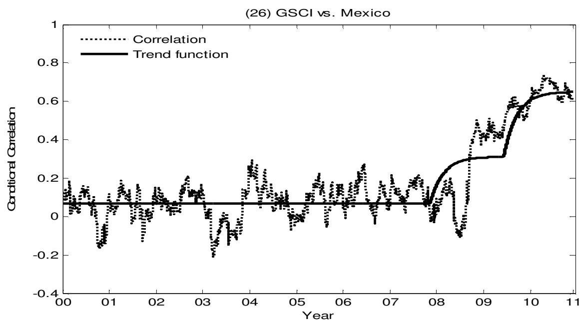

(21) GSCI vs. Israel
Correlation
Trend function
Conditional Correlation
Year

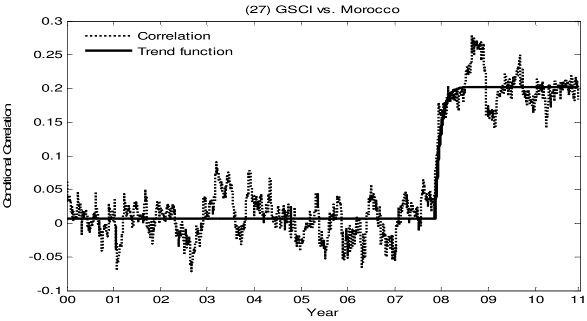

(22) GSCI vs. Italy
Correlation
Trend function
Conditional Correlation
Year

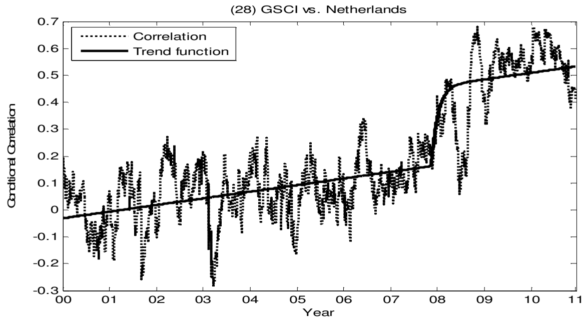

(23) GSCI vs. Japan
Correlation
Trend function
Conditional Correlation
Year

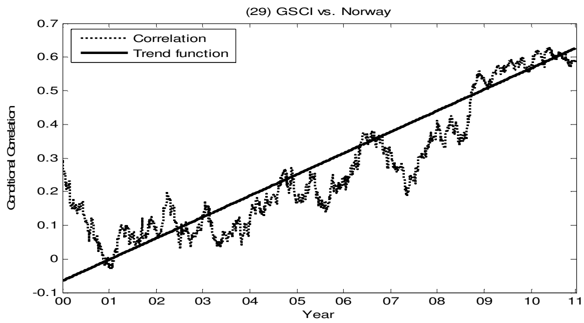

(24) GSCI vs. Korea
Correlation
Trend function
Conditional Correlation
Year

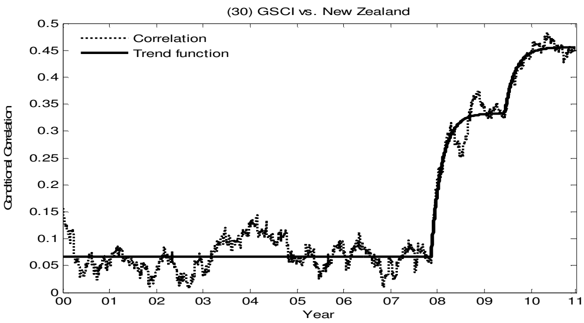

(25) GSCI vs. Malaysia
Correlation
Trend function
Conditional Correlation
Year

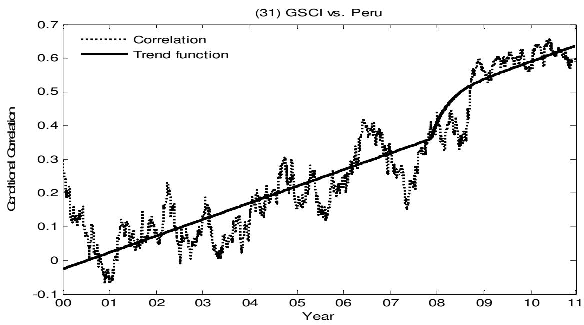

(26) GSCI vs. Mexico
Correlation
Trend function
Conditional Correlation
Year

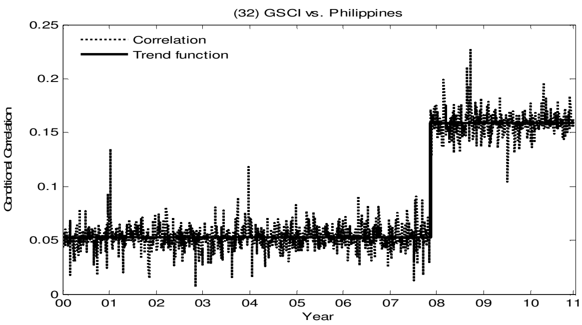

(27) GSCI vs. Morocco
Correlation
Trend function
Conditional Correlation
Year

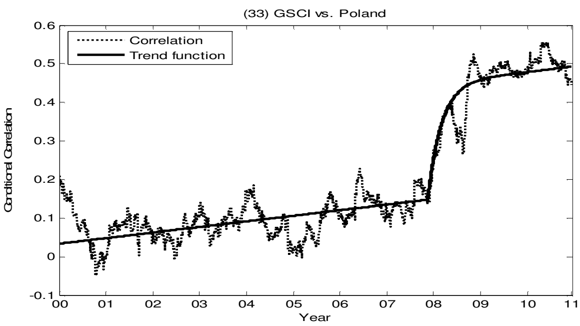

(28) GSCI vs. Netherlands
Correlation
Trend function
Conditional Correlation
Year

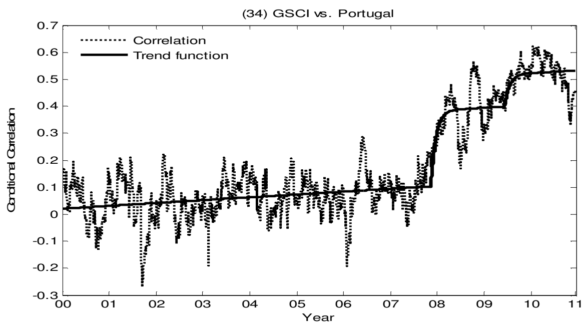

(29) GSCI vs. Norway
Correlation
Trend function
Conditional Correlation
Year

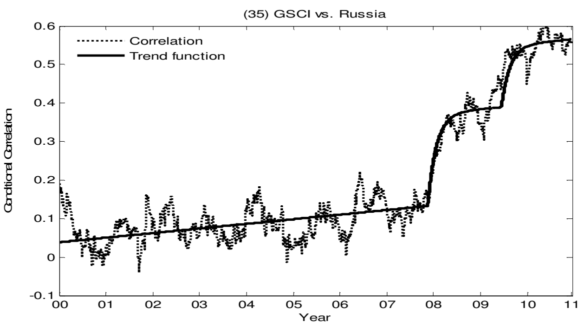

(30) GSCI vs. New Zealand
Correlation
Trend function
Conditional Correlation
Year

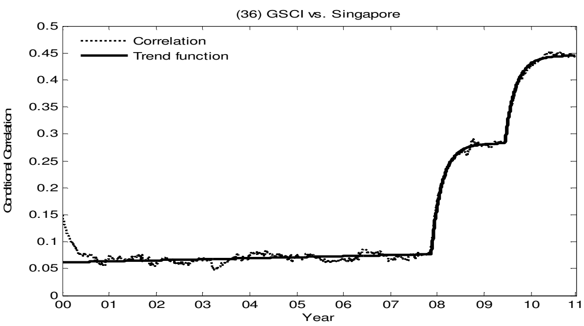

(31) GSCI vs. Peru
Correlation
Trend function
Conditional Correlation
Year


(32) GSCI vs. Philippines
Correlation
Trend function
Conditional Correlation
Year

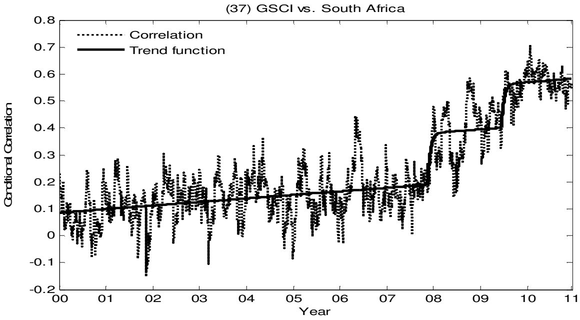

(33) GSCI vs. Poland
Correlation
Trend function
Conditional Correlation
Year


(34) GSCI vs. Portugal
Correlation
Trend function
Conditional Correlation
Year

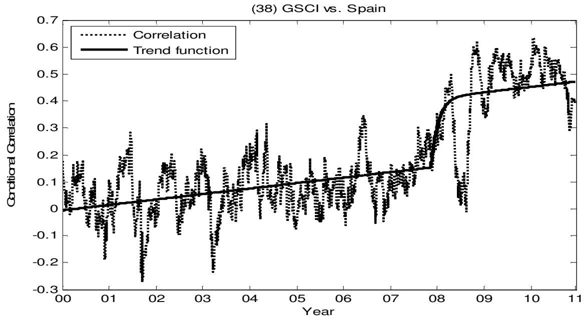

(35) GSCI vs. Russia
Correlation
Trend function
Conditional Correlation
Year


(36) GSCI vs. Singapore
Correlation
Trend function
Conditional Correlation
Year

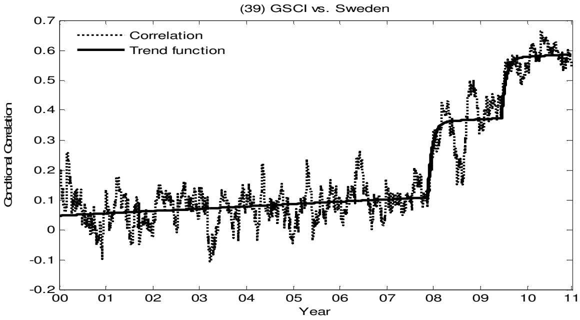
(37) GSCI vs. South Africa



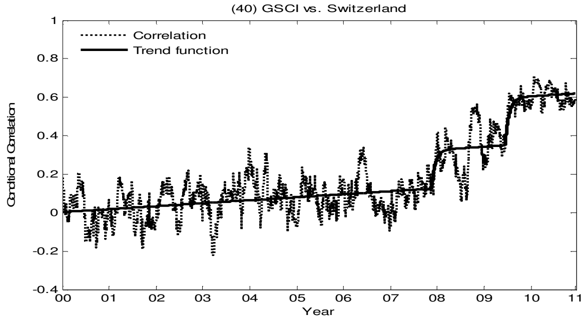
(38) GSCI vs. Spain



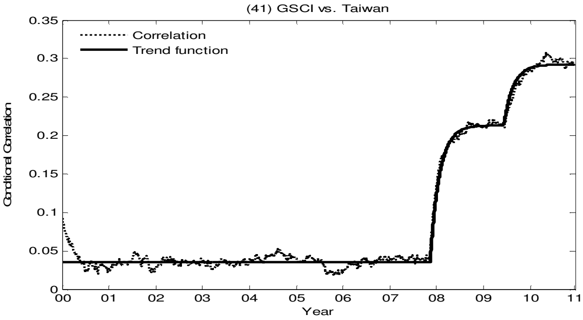
(39) GSCI vs. Sweden



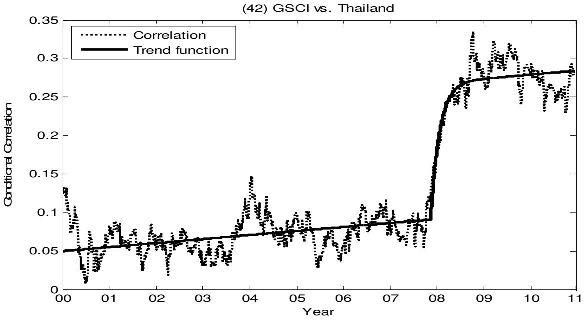
(40) GSCI vs. Switzerland



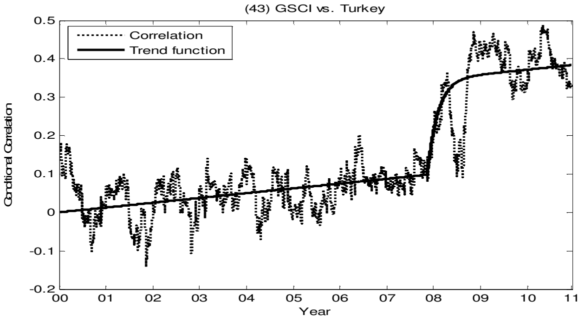
(41) GSCI vs. Taiwan



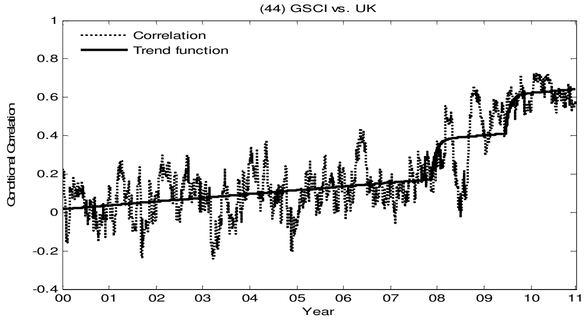
(42) GSCI vs. Thailand



(43) GSCI vs. Turkey



(44) GSCI vs. UK



(45) GSCI vs. US