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Research Article

Analysing correlation between the MSE index and global stock markets

R. Ellul[*1]
[1]*Economics and Monetary Analysis Department of the Central Bank of Malta.*

Abstract. The paper investigates the time-varying correlation between the Malta Stock Exchange (MSE) index, and five major international stock markets. An MGARCH-DCC approach is employed to measure the degree to which the MSE moves with other stock markets. Daily returns on these six stock exchange indices were computed and used to calculate dynamic conditional correlations (DCCs) between the markets. The results indicate that the local stock market appears not to be driven by the same forces that shape foreign stock markets, implying that local dynamics shape returns on the Exchange, rather than foreign events.

Keywords: MGARCH, DCC, correlation, financial integration, stock indices, Malta stock exchange index (MSE)

1 Introduction

A study on the degree to which the Malta Stock Exchange (MSE) index is correlated with other stock exchange indices is useful to gauge financial integration between the local and the global economies. Any meaningful analysis of such correlation ought to however account for changes in such a relationship between the local and foreign stock markets, particularly as the Maltese economy has experienced a significant transition – with an increased importance of financial services over the past decades. Using established financial econometric techniques, this study attempts to investigate the degree of correlation between the local stock exchange index, and major foreign indices.

2 Literature Review

Efficient portfolio management theory tends to recommend diversification between geography and economic sectors. Over the past thirty years, cross-border capital flows have increased in size and changed in scope, as countries sought to liberalise financial markets while market players resorted to ever more complex financial innovations. Equity market integration and correlations have, therefore, risen rapidly. A number of financial econometric techniques are employed to measure these relationships. This study focuses on multivariate, generalised autoregressive conditional heteroskedasticity (MGARCH) models, particularly dynamic conditional correlation, (DCC). The seminal studies on volatility spillovers and correlations between stock markets focus on the 1987 Stock Market Crash, with King and Wadhwani (1990), and Hamao, Masulis and Ng (1990) analysing dynamics both before and after the crash.

A significant branch of the literature attempts to measure symmetries in volatility, with Koutmos and Booth (1995), amongst others, showing that markets have different reactions to positive and negative volatility shocks. Lin, Engle and Ito (1994), prove that spillovers between markets are different for global and local shocks. An MGARCH model is used by Theodossiou and Lee (1993) to study the relationship between major stock markets. Empirical studies have also focused on correlations and spillovers between emerging markets. Worthington and Higgs (2004) used a constant conditional correlation (CCC) MGARCH specification to analyse correlations in returns of emerging Asian markets and developed markets.

Unlike DCC models, the premise of CCC involves modelling comovements between heteroskedastic time series by allowing each series to follow a separate GARCH process, to then impose restrictions on the conditional correlations between the GARCH processes - forcing them to be constant, following Bollerslev (1990). This reduces the number of parameters to be estimated, but may be too strict in many empirical applications. Thus, CCC models assume correlations to be constant, while the DCC approach allows these to change. The latter methodology also gives information on the

*Correspondence to: Reuben Ellul (ellulr@centralbankmalta.org)

nature of the correlation relationship: A temporary increase in DCC correlations indicates contagion effects, while a change in correlations which leads to a new and stable level in conditional correlations implies interdependence. The DCC methodology therefore allows inferences on whether there are changes in the underlying relationship between the modelled series, and also sheds light on the nature of the relationship.

Bekaert, Harvey and Ng (2005) examine the effect of highly integrated global stock markets on the returns, cross market correlations and volatilities of emerging stock markets. Their results, along with analysis by Sok-Gee and Karim (2010), indicate high correlation and volatility spillovers. More recently, these techniques have been applied in a number of studies aimed to gauge the effect of the 2009 financial crisis, or the subsequent European sovereign debt crisis on particular markets or overall stock exchanges.[2]

There are few analyses that include the MSE or attempt to address the issue of correlations between the local index and global financial markets. An exception is Wang, Podobnik, Horvatić and Stanley (2011), which explains cross-correlations by introducing a global factor model (GFM).[3] The authors find that Malta's stock index, along with those of Iceland, Israel, Qatar and a number of other countries, are weakly bonded with other national financial markets, corroborating this study's hypothesis. However, their methodology models only the magnitude cross-correlations when modelling the global factor, choosing to simplify their approach by ignoring the effect of autocorrelation in returns. By allowing only for magnitude cross-correlations, the GFM model focuses on strong market crash episodes and might be missing on the correlation dynamics otherwise captured by an MGARCH specification.

An additional study by Allen, Powell and Golab (2010), seeks to measure volatility and correlation in stock indices between emerging European markets. The study finds that the MSE has the lowest volatility, and is characterised by "self-directed independent behaviour" when compared with eleven European stock indices in Central and Eastern Europe. This study goes beyond Allen et al. (2010), who specify a simpler GARCH(1,1) model without allowing for CCC or DCC parameters. Additionally, most of the countries included in the pairwise correlations in this study have few economic or historical ties with Malta, other than having joined the European Union on the same day in May 2004.

[2]See Markwat, Kole and van Dijk (2009), Naoui, Liouane and Brahim (2010), Arezki, Candelon and Sy (2011).

[3]This is a general method which the authors argue can be applied to a range of phenomena including seismology and atmospheric geophysics.

3 Data

The MSE operates within the parameters of the Malta Stock Exchange Act of 1990, and began its trading operations in January 1992. The market fulfils its role to raise capital finance, with the Exchange providing the structures for admission of financial instruments to its recognised lists. These are then traded on a secondary market. As of January 2015, the regular market on the Exchange lists slightly over thirty-five securities, of which twenty-three are equities. The market is dominated by banks and Malta Government Stock listings. Azzopardi and Camilleri (2004) find no significant market making, short sale or derivatives activities conducted on the Exchange.

In fact, Camilleri (2005) describes the MSE as one of the smallest exchanges in Europe, with a limited number of daily transactions due to the country's low population; according to this study, this small size makes Malta "relatively unimportant" when compared with other emerging markets – especially as its size effectively decreases the likelihood of "inward financial investment flows from overseas." Thus, the limited size and low liquidity of the local market is seen as a possible reason for the isolation of the Exchange. The total market capitalisation value of the index stood at €10.3 billion at the end of 2014, with a market turnover value of €940 million. In the same year, 44.5 million shares changed hands in 25,657 transactions.

These figures cannot be compared, both in terms of size of the market and its liquidity, to any other major stock exchange, with the market capitalisation of the whole exchange comparable in size to that of a large company listed on an international stock exchange. The number of listed equities has increased very slightly over time, with a few companies seeking admission to the market from time to time. Although one might expect that once some particular size or liquidity thresholds are reached the relative isolation of Malta's stock exchange might change, the small size of the local economy and population are seen to constrain growth of the Exchange.

The MSE Index, the single index computed by the Exchange, is characterised by broad, cyclical movements, with a significant surge in the first quarter of 2006, (see Figure 1), following which the index contracts and stabilises at a lower level. Two peculiar spikes appear in the index, appearing on 03/01/2001 and 03/01/2002. These relate to two well documented incidents on the local exchange, pertaining to administrative changes which translated to significant drops on the Exchange.[4] While data for the MSE is available from as early as 1992, the need to compare the indices with a common currency limited the sample to the daily closing prices from January 1999, the date of the establishment of the euro as an accounting currency, to mid-January 2015, for a total of 3950 observations.[5]

4 Methodology

4.1 Estimating Dynamic Correlations

Dynamic correlations between stock exchange indices explain whether market prices move together, allowing the analysis of market interdependencies. Thus, for example, an exogenous shock will drive correlated markets together. On the other hand, a market with low correlation with another implies that market price movements are more explained by market-specific, or internal, events rather than events on the other markets.

Additionally, literature on cross-market contagion indicates that temporary decreases or increases in correlations following a shock in one market imply contagion effects between stock markets, while 'level shifts' in correlations imply interdependence. This analysis uses an MGARCH model to calculate DCCs between stock indices.

This technique is preferable to the more traditional studies of correlations in that it does not give equal weights to past observations, as in moving-windows models. This model incorporates time-varying volatilities from the estimated GARCH processes. Past realisations of market volatilities and correlations will affect the estimated conditional correlations, giving more weight to recent observations and less to more distant ones.

Dynamic conditional correlations are estimated in three stages. The first step requires a demeaning process, usually via autoregressive-moving average (ARMA) models, in order to calculate residual returns. In the second step, these returns are modelled as autoregressive conditional heteroskedasticity (ARCH) or, if required, GARCH processes.

These residuals follow the standard MGARCH-DCC representation, see Engle (2000). Letting $\boldsymbol{r_t} = [r_{1,t}, \ldots, r_{k,t}]'$ be the vector of demeaned variables in the DCC model,

$$\boldsymbol{r_t}|\phi_{t-1} \sim N\left(\boldsymbol{0}, \boldsymbol{D_t}\,\boldsymbol{R_t}\,\boldsymbol{D_t}\right) \tag{1}$$

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

for $i = 1, \ldots, k$.

$$\boldsymbol{\varepsilon_t} = \boldsymbol{D_t}^{-1}\boldsymbol{r_t} \tag{3}$$

$$\boldsymbol{R_t} = diag\left(\boldsymbol{Q_t}\right)^{-1/2}\left(\boldsymbol{Q_t}\right) diag\left(\boldsymbol{Q_t}\right)^{-1/2} \tag{4}$$

$$\boldsymbol{Q_t} = \left(1 - q_a - q_b\right)\overline{\boldsymbol{Q}} + \alpha\left(\varepsilon_{t-1}\right)\left(\varepsilon_{t-1}\right)' + \beta\boldsymbol{Q_{t-1}} \tag{5}$$

where $\boldsymbol{R_t}$ in (1) is a $k \times k$ matrix of time-varying correlations and $\boldsymbol{D_t}$ is a diagonal matrix of standard deviations, $\sqrt{h_{i,t}}$, which derives from univariate GARCH models (or other GARCH variants) as in (2). The variables are then standardised by the respective standard deviations by dividing them, see (3). This standardisation enables the specification of the correlation estimator, see (4) and (5). In (5), $\overline{\boldsymbol{Q}}$ is the unconditional covariance matrix of the standardised variables, $\overline{\boldsymbol{Q}} = E\left(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'}\right)$.

The coefficients q_a and q_b, which measure the effect of time-varying correlation, capture the effect of previous shocks and lagged dynamic conditional correlations. Thus, in terms of interpretation, q_a measures the sensitivity of the correlations to shocks and q_b measures the lagged effect of these shocks, which can be viewed to be the persistence in their volatility.

The DCC parameters are then estimated via maximum likelihood methods.[6] After modelling the GARCH parameters as in (2), these are then used in the final stage to estimate the DCC parameters in (5). Additionally, the methodology allows testing of constant correlations between indices over time.

4.2 Empirical Procedure

Six stock exchange indices were analysed for correlation, the MSE, the *Cotation Assistée en Continu - Quarante* (CAC40), the *Deutscher Aktienindex* (DAX), the *Dow Jones* (DJ), the *Financial Times Stock Exchange* index, (FTSE100) and the *NASDAQ* index. A priori, one expects low correlation between the MSE index and the other stock exchanges, and higher correlation between the other stock indices. Geographically closer stock indices can be expected to have higher correlation than more distant ones.

Daily data for these six indices were obtained from *Yahoo! Finance* and the MSE index website. The indices were adjusted for working days, based upon the availability of Maltese data.[7] January 2004 was used as a base month for the six indices. The series were converted into euro, using daily foreign exchange rates.[8] The data were transformed as daily returns as,

$$dmr_{k,t} = 100\log\left(\frac{P_{t+1}}{P_t}\right) \tag{6}$$

[4]See Mifsud, A., "Meltdown", Times of Malta, 22/01/2001. Additionally, a number of financial market liberalisation measures came into effect in January 2002. These may have altered investors' portfolio optimisation strategies in that year. Liberalisation of capital controls took place gradually until 2004.

[5]Malta joined the European Union, and thus, the Economic and Monetary Union (EMU) in May 2004. Malta became a member of the Euro area, and a full member of the third stage of the EMU in January 2008. The MSE index reflected this change, with the final conversion rate between the Euro and the Maltese Lira (MTL) set at 1 EUR = 0.4293 MTL.

[6]Quasi-maximum likelihood (QML) methods are applied if the variables are not normal.

[7]On closed market days, unavailable observations were replaced with the latest closing price of the stock index.

[8]When unavailable, the last available exchange rate was applied.

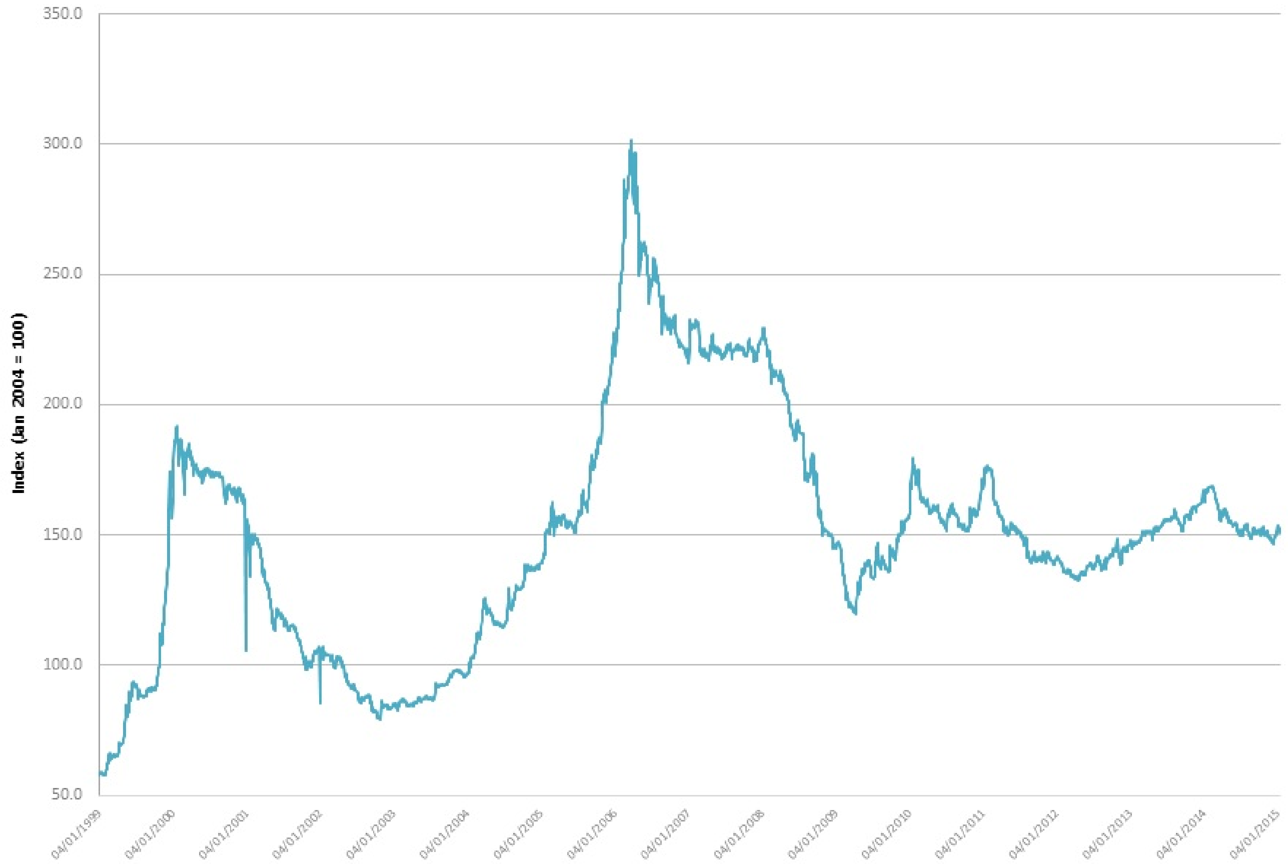

Figure 1: Malta Stock Exchange index (Jan 2004 = 100).

for $k = 1, \ldots, 6$ and $t = 2, \ldots, 3950$, where $dmr_{k,t}$ is the daily market return from the stock index k, and t is a time subscript. These daily returns were then modelled as ARMA equations, with a maximum allowed lag of 7 on both the AR and MA components.[9] Lag selection was based upon the Akaike information criteria.

The residuals from these univariate equations were then modelled as ARCH/GARCH models, following Engle (2000).[10] The MSE residuals were modelled as an ARCH(4) GARCH(1) model, the CAC40 as an ARCH(2) GARCH(3) process, the DAX was modelled as an ARCH(2) GARCH(1) process, the DJ as an ARCH(3) GARCH(3) equation, the FTSE as an ARCH(4) GARCH(2) process and the NASDAQ as an ARCH(4) GARCH(4) process. The standardised residuals for each modelled equation were stored and used as inputs in an MGARCH-DCC(1,1) process. Upon inspecting the standardised residuals for the MSE index, two dummy variables were created to account for the two spikes observed in the index. These were included in the mean equation for the MSE equation. Additionally, the need to calculate cross-correlations in an MGARCH-DCC(1,1) framework required the re-sampling of the observations to ensure balanced observations.[11] The specific mean equations as specified in this estimation included a constant term and lagged values of all the indices included in the study,[12] that is,

$$r_{k,t} = \theta_0 + \theta_1 r_{1,t-1} + \cdots + \theta_k r_{k,t-1} + \theta_{k+1} d1 + \theta_{k+2} d2 + \varepsilon_t, \quad (7)$$

where $r_{k,t}$ are the standardised residuals from the GARCH processes described above, θ_0 is a constant, $\theta_1 r_{1,t-1}$ to $\theta_k r_{k,t-1}$ are the lagged values of the standardised residuals from all stock indices, and $d1$ and $d2$

[9] The univariate models for the six indices were ARMA(5,6) for the MSE, ARMA(7,4) for the CAC40, ARMA(7,7) for the DAX, ARMA(5,7) for the DJ, ARMA(6,7) for the FTSE100 and ARMA(7,7) for the NASDAQ index.

[10] An automated lag selection program, based on a freely available add-in found with the econometric package EViews was coded for this purpose. The lag length selection was again based upon the Akaike information criteria.

[11] As the original ARMA models included different number of lags, the resulting residuals were unbalanced. The re-sampling entailed the removal of the first 17 observations from the sample.

[12] Equations and output results are available from the author upon request. The preliminary stages of the analysis were conducted in EViews package, the DCC estimation was carried out using STATA.

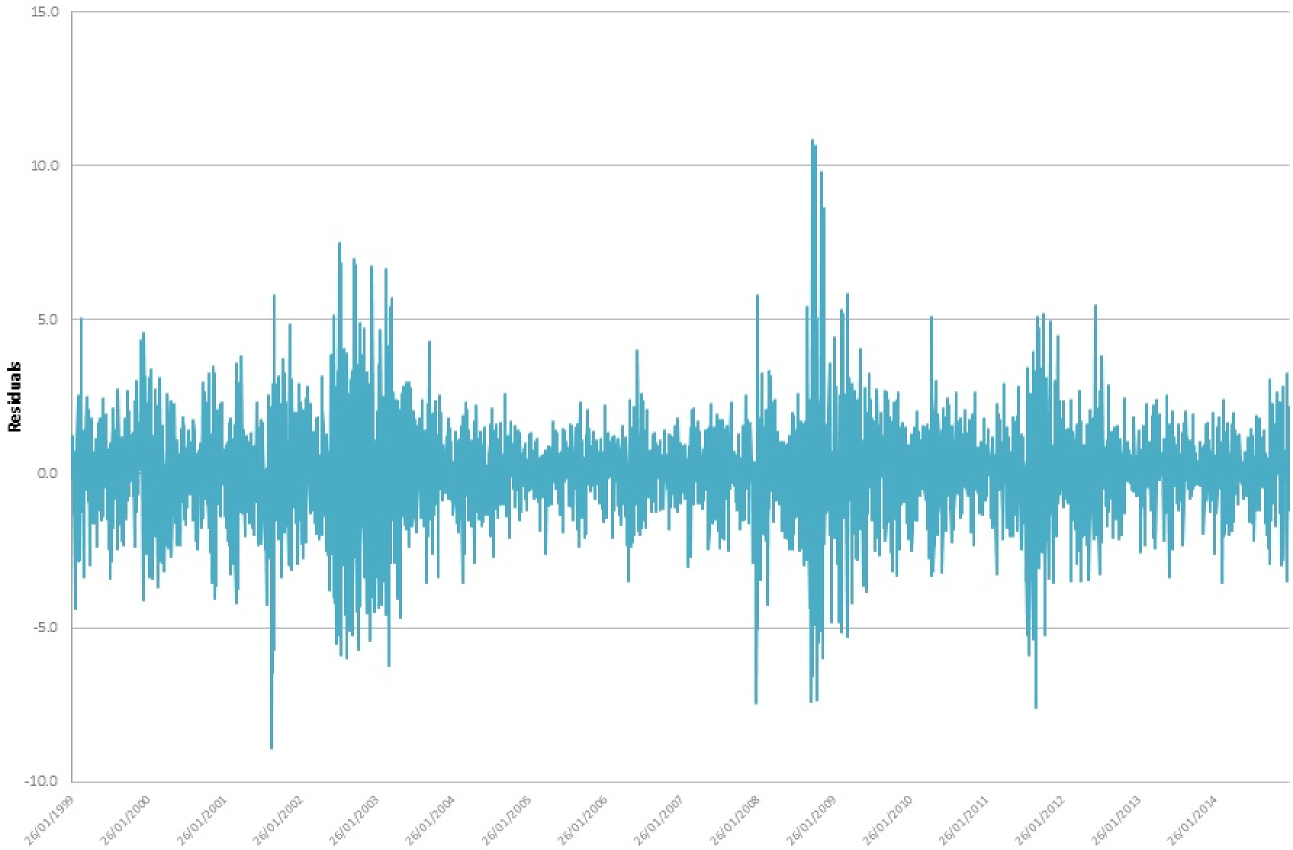

Figure 2: Residuals from DAX ARMA process (left) – note ARCH effects in the series.

are dummy variables accounting for the two extreme events in the MSE, used for the MSE equation, as described above.

5 Results

The parameters indicate a high persistence of volatility. The effects of time-varying conditional quasi-correlations, embodied by the parameters $\lambda 1$ and $\lambda 2$, are also highly significant. Additionally, while the $\lambda 1$ coefficient is very close to zero, indicating that there is low sensitivity in the correlations to shocks, the coefficient $\lambda 2$ is larger and close to one. This again confirms that the dynamic correlation exhibits a high degree of persistence. These statistical results indicate that there is significant dynamic correlation in the data. All the ARCH parameters, denoted as α, are significant while most of the coefficients for the lagged squared error variance, β, are significant except for the CAC40 and DAX indices.

The DCC MGARCH model reduces to a CCC MGARCH model if $\lambda 1 = \lambda 2 = 0$. A Wald test was carried out, rejecting the null hypothesis that $\lambda 1 = \lambda 2 = 0$ at all conventional levels. The test rejects the null hypothesis that the $\lambda 1$ and $\lambda 2$ parameters estimated in the DCC methodology are equal to zero. The model can thus be better represented using constant conditional correlation. Time-invariant conditional correlation, as assumed by the CCC MGARCH, model is too restrictive for these series, as the correlations between these indices are changing over time. The results can be seen below.

$$
\begin{aligned}
H0 = \lambda 1 = \lambda 2 = 0 \\
(1) \qquad \lambda 1 - \lambda 2 = 0 \\
(2) \qquad \lambda 2 = 0 \\
\chi^2(2) = 6.9e^5 \\
\text{Prob} > \chi^2 = 0.00
\end{aligned}
$$

The DCCs of the MSE index against the other markets from January 1999 to January 2015 can be seen in Figure 4. The estimates suggest that there are no high correlations between Malta and international stock indices. In most of the cases for correlation involving the

Figure 3: Residuals from DAX ARCH(2) GARCH(1) process (right).

MSE, the estimate is not higher than 0.2.[13] The interpretation of these figures is that the Maltese equity market is relatively isolated from movements in international stock equity markets. This means that local returns appear to be influenced internally, and not by international events.

High volatility of conditional correlations can be observed between returns from the local stock index and the other indices, meaning that the correlation (co-movement) between stock markets returns varies with time. Secondly, the trend of correlation between the MSE index and other stock markets is not rising, such that the local stock index has not become more integrated over time.

As expected, the other stock exchange indices exhibit higher values of correlation, with the correlation between the DAX and the CAC40 topping the list with figures around 0.7–0.9. The average conditional correlations between the stock exchange indices are presented in Table 2.

While correlations between the above-mentioned continental stock exchanges are the highest, the correlation between the CAC40 and the DAX with the DJ index stands at a more modest 0.57. Additionally, the correlation between the FTSE100 and the European stock indices is higher than that with the DJ. This follows a priori geographic expectations.

These average of the DCCs over the period are very similar to the standard correlation obtained from simpler methods. However, the DCC method highlights periods of high volatility, in particular the contagion and transmission of shocks between markets in episodes of financial stress, as seen in Figure 4 above. This would mean that while simple correlation methods return results which are almost identical to the average of the DCCs obtained through this methodology, reliance on them would ignore transmission mechanisms and contagion episodes between the modelled stock market series.

[13] An interesting observation accounts for the shock seen on 27/02/2007, with all DCC estimates for the six indices exhibiting a particular upwards spike. On that day, international stock markets experienced sustained and negative pressure, with the DJ alone losing above 400 points, in what was termed *The Chinese Correction* as all indications suggested the sell-off began on the Shanghai stock exchange with a 9% drop. On the same day, Freddie Mac issued a press statement, effectively declaring it would stop purchasing sub-prime mortgages from borrowers who had a "high likelihood" of not meeting their monthly payments.

Table 1: Output from MGARCH-DCC(1,1) framework; the table reports the empirical results for the DCC model using the in-sample data, estimated parameters result for the constant ϖ, the ARCH effect parameter α, the GARCH effect parameter β, and the log-likelihood. $\lambda 1$ and $\lambda 2$ are equivalent to the parameters q_a and q_b mentioned above, and are used to test for CCC.

			Log likelihood	−24216.14
			Wald χ^2 (38)	1506.59
			Prob > χ^2	0.00
	$N = 3933$	**Parameters**	**z-Statistic**	**p-value**
MSE	ϖ	1.51	25.24	0.00
	α	0.01	12.74	0.00
	β	−0.84	−14.97	0.00
CAC40	ϖ	1.50	6.56	0.00
	α	0.03	3.27	0.00
	β	−0.32	−1.69	0.09
DAX	ϖ	1.23	7.92	0.00
	α	0.04	3.92	0.00
	β	−0.11	−0.84	0.40
DJ	ϖ	1.83	11.58	0.00
	α	0.02	2.75	0.01
	β	−0.67	−5.00	0.00
FTSE	ϖ	0.27	2.42	0.02
	α	−0.01	−2.46	0.01
	β	0.78	8.25	0.00
NASDAQ	ϖ	1.76	10.81	0.00
	α	0.03	3.01	0.00
	β	−0.64	−4.60	0.00
	$\lambda 1$	0.02	18.28	0.00
	$\lambda 2$	0.96	495.99	0.00

Table 2: Average dynamic conditional correlations between stock exchange indices; these are calculated by averaging the conditional correlations derived from the DCC methodology over the sample range. The values thus obtained are virtually identical to simple correlations calculated between the filtered stock exchange returns series.

	MSE	**CAC40**	**DAX**	**DJ**	**FTSE100**	**NASDAQ**
MSE	1.00	0.02	0.02	0.01	0.03	0.01
CAC40		1.00	0.88	0.57	0.76	0.45
DAX			1.00	0.57	0.73	0.48
DJ				1.00	0.58	0.83
FTSE100					1.00	0.45
NASDAQ						1.00

6 Conclusion

This study has confirmed the apparent lack of correlation between the MSE and other international equity markets highlighted in the literature. The reasons why there is no underlying correlation, especially if these are linked with local share-ownership and investment strategies, ought to be investigated. An avenue of further research, particularly interesting for financial stability purposes, is an analysis of correlation between equity prices and the performance of domestic banks and international ones.

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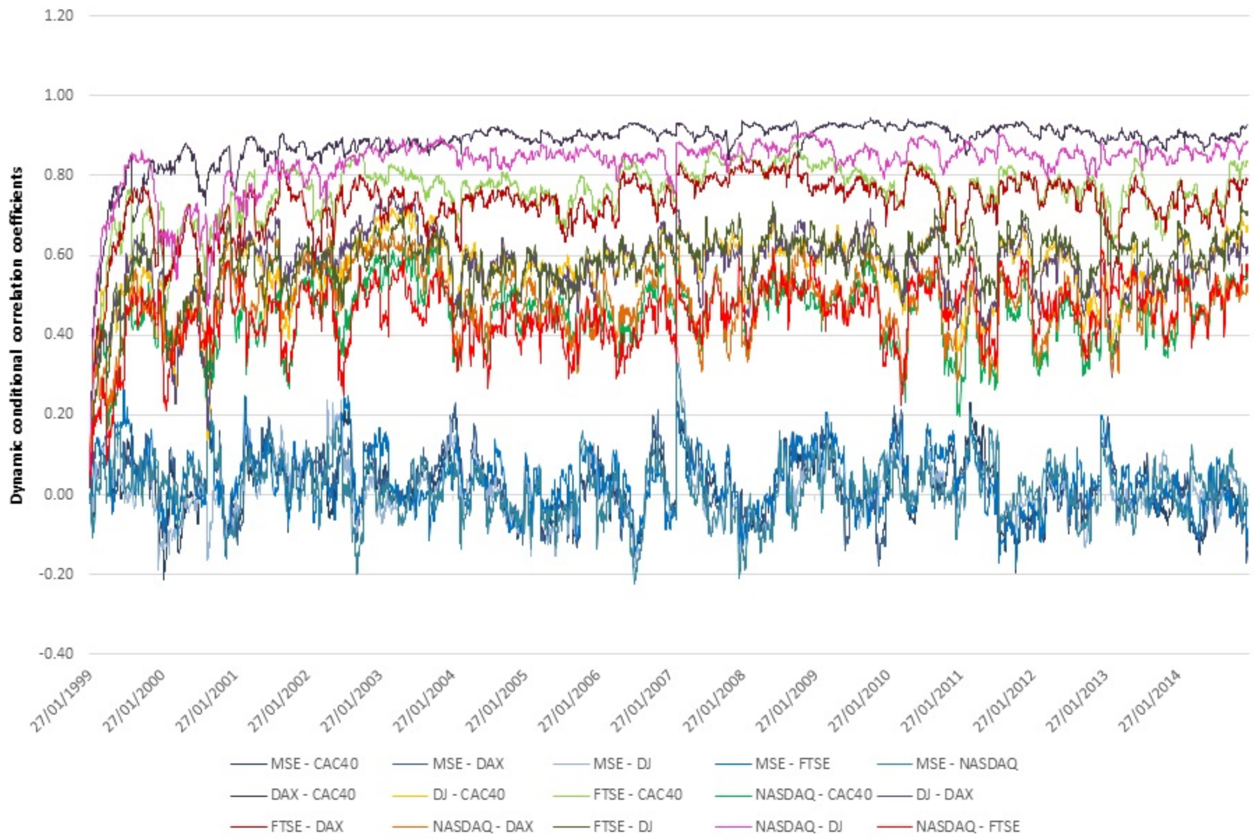

Figure 4: Dynamic conditional correlations for the stock exchange indices being studied. Notice that the conditional correlations against the MSE index all tend to hover around zero.

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