

SECTORS STOCK INDICES AGGREGATE CORRELATIONS AND EXPECTATIONS: EVIDENCE FROM THE GREEK STOCK MARKET

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Abstract

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Based on the cyclical movements of the Athens Stock Market, the paper empirically examines the behavior of seven sectors (markets) namely: industry-services, emporium, construction, petroleum, telecommunications, food-beverages, and banks. Specifically using daily observations from January 2006 to August 2017, we estimate a dynamic equicorrelation multivariate GARCH model (DECO-MGARCH) developed by Engle and Kelly (2012), to analyze the dynamic behavior of these sectors. Furthermore, using time-dependent entropic measures we examine empirically the uncertainty (expectations) regarding the correlation behavior of these seven sectors. The empirical results are in line with previous findings (Tsai & Chen, 2010; Garnaut, 1998) and provide evidence supporting the view of high correlations during periods of crises. In addition, the dynamic entropy shows that the expectations of market participants were more concentrated (less spread out) during these periods of crises. Therefore, the empirical evidence of the paper supports the view that market participants share the same opinions (entropy exhibits low uncertainty) during crises and therefore are acting in a similar fashion (exhibiting high correlation).

Keywords: Financial Markets and Institutions, Athens Stock Market, Dynamic Equicorrelation, GARCH Model, Entropy, Market Sectors, Investors' Risks and Returns

Authors' individual contribution: Conceptualization — A.N. and I.P.; Methodology — A.N. and I.P.; Software — I.P.; Validation — A.N. and I.P.; Formal Analysis — I.P. and S.P.; Investigation — I.P. and S.P.; Writing — Original Draft — I.P. and S.P.; Writing — Review & Editing — S.P.; Supervision — A.N. and I.P.

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1. INTRODUCTION

The issue of correlation between different stock market sectors, between different stocks, or between stock markets of different regions has been

thoroughly researched. The correlation among stocks and various sectors in a stock market affects investors' risks and returns and has profound implications on selecting diversified stock market portfolios. Many studies have shown that equity

return correlations do not remain constant over time. They tend to decline in bull markets and to rise in bear markets (De Santis & Gerard, 1997; Ang & Bekaert, 1999; Longin & Solnik, 2001). Correlations also tend to rise as the integration of the international equity market rises (Erb, Harvey, & Viskanta, 1994; Longin & Solnik, 1995).

Numerous researchers have noted the linkage between volatility and correlations and tried to determine the nature of this linkage. High levels of volatility in correlation lead to the application of multivariate GARCH-based methodologies.

In this paper, we estimate a dynamic equicorrelation multivariate GARCH model (DECO-MGARCH) to analyze the dynamic behavior of seven Athens Stock Exchange sectors (markets) using daily observations from January 2006 to August 2017. As shown by Clements, Scott, and Silvennoinen (2016) the equicorrelation type of models perform consistently well across various sample sizes and this is particularly true during periods of market turbulence. Furthermore, the assumption of equicorrelation is found to be very useful dealing with large portfolio allocation problems. The sectors we examined in this paper are industry-services, emporium, construction, petroleum, telecommunications, food-beverages, and banks. Furthermore, we used time-dependent entropic measures to empirically examine the uncertainty (expectations) regarding the correlation behavior of these seven sectors. Our findings seem to support the view that high correlations are present during periods of crises.

The novelty of this paper is that studies in this area focus on developed markets and only very few examine developing and emerging markets and none employ entropy measures to calculate correlations between sectors' indices.

The paper is structured as follows. Section 2 provides the literature review. Section 3 presents the performance data of the seven Greek stock market sectors under investigation and in Section 4 we describe our research methodology and model specification. Section 5 summarizes our results and discussion and Section 6 presents our conclusions.

2. LITERATURE REVIEW

The assertion that correlation increases during times of high market volatility are very well documented in the literature (Karolyi & Stulz, 1996; Ramchand & Susmel, 1998; Longin & Solnik, 2001; etc.). A number of studies have examined the impact of a crisis on correlation levels. Tsai and Chen (2010) and Garnaut (1998) examined the impact of both financial and non-financial crises on the correlation among financial markets within the U.S. They found evidence suggesting the crises resulted in significant short-term increases in correlation. Furthermore, Schwebach, Olienyk, and Zumwalt (2002), Cho and Parhizgari (2008) and Medo, Yeung, and Zhang (2009) reported similar results for a number of developing markets. Therefore, the 2007 financial crisis provides an excellent example to determine how and in what magnitude correlation is affected.

Niklewski (2014) suggests that correlation seems to be greater in emerging/developing markets. He argues that increases in correlation may be the consequence of two factors, first

the tightening of regulations in combination with the deleveraging that took place in financial markets and sectors worldwide, and second the impact of the crisis on relative market conditional volatilities. He also finds that market conditions have a big impact on correlation, which in turn have a considerable impact on portfolio weights, but he reports no significant increase in portfolio returns.

The problem of constant correlation is solved by the dynamic conditional correlation GARCH (DCC-GARCH), first suggested by Engle (2000). The mathematical framework of this model firstly estimates the conditional standard deviations through the univariate GARCH and secondly, it calculates the time-varying correlations relying on lagged values of residuals and covariance matrices (Engle & Sheppard, 2001). After that, the conditional covariance matrix is formulated by using conditional standard deviations and dynamic correlations.

The first adaptation of a GARCH process is carried out by Bollerslev, Engle, and Wooldridge (1988). They employ the univariate GARCH process to do multivariate parameterization. However, when the sample size is very large the computational problems are quite considerable and thus it is hard to achieve a feasible estimation.

Bollerslev (1990) introduces a variation of this GARCH model, namely, the constant conditional correlation GARCH (CCC-GARCH) model. In this framework, standard deviations of each asset are produced by a univariate GARCH process. The standard deviations within the covariance matrix are calculated relying on the GARCH constraints.

The DCC-GARCH model is a very well-structured model employed to estimate the time-varying covariance matrix. However, when we have a very large number of observations the estimation of conditional correlation matrix becomes very difficult. Engle and Kelly (2012) reduced the burden of large-scale parameterization and thus reducing the scale of estimation by averaging pair dynamic correlations. This process is called dynamic equicorrelation GARCH (DECO-GARCH).

Kearney and Poti (2005) examined correlation dynamics using daily data from 1993 to 2002 on the five largest Eurozone stock market indices. They estimated conditional correlations using the symmetric and asymmetric dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model and their results suggested that there are very small benefits to be gained in diversifying across Eurozone market indices, although there were significant gains to be exploited in diversifying across different stocks. Meric, Ratner, and Meric (2008) studied the portfolio diversification implications of the co-movements of sector indexes in the U.S., the UK, German, French, and Japanese stock markets in bull and bear markets (1997-2002). Their findings indicated that all the sectors are highly correlated with each other and with the national benchmark stock market index in France and Japan in the bull market. They found that, in a bull market, investors can obtain more benefits with global diversification than with domestic diversification. Cao, Long, and Yang (2013) examined the relationship between the stock market indices of China's stock market (July 2007-December 2012). They divided the period into two

stages. One stage represented the drastic shock periods in 2007 and 2008, and the other represented the general ups and downs periods. In the first stage when the market experienced drastic ups and downs, the sector indices tended to rise or fall together and exhibited very close correlations between each other. In the second stage, however, much smaller correlations appear, and the stock price indices reflected the cyclical characteristics of the real sector economy.

Yilmaz (2010) used both DCC- and DECO-GARCH methods to track the performance of global minimum variance portfolios investing in the Istanbul Stock Market. His results seem to suggest that the performance of those portfolios estimated by DCC- and DECO-GARCH outperformed all other portfolios and furthermore, the performance of the portfolios improved when the sample period was extended.

Kang and Yoon (2019) estimate three different vector autoregressive multivariate GARCH (VAR-MGARCH) models in an effort to address the issue of correlation and volatility transmission between Chinese stock and commodity futures markets from August 2004 to May 2016. They found that the DCC-GARCH model performed best in estimating the dynamic conditional correlation. The findings suggested that in optimal portfolios, stocks should outweigh commodity futures and optimally weighted commodity-stock portfolios may help investors reduce risks. As regards portfolio risk management analysis, the study calculates optimal hedge ratios for different commodities and thus determining optimal portfolio weights for reducing portfolio risk.

Gulay and Emec (2018) compared the forecasting performances of different variance stabilization methods (NoVaS) and various GARCH models for a number of stock markets and found that NoVaS methods exhibited better out-of-sample forecasting performance than GARCH-type models.

Alkan and Cicek (2020) employed a BEKK (Baba, Engle, Kraft and Kroner) parameterization of the multivariate GARCH model to test for spillover effects in Turkish financial markets between 2006 and 2018. Their results supported the existence of a strong spillover effect from global markets to Turkish stock and bond markets and from the Turkish stock and exchange markets to the bond market. Strong volatility spillover effects between each market pair were also present. Therefore, these results indicate that a shift in volatility in a global market spreads to other domestic markets almost immediately.

Kang, McIver, and Yoon (2017) in their study investigated the spillover effects among six commodity futures markets by employing the multivariate DECO-GARCH model and a spillover index. They examined the period from January 2002 to July 2016 and included six commodities namely gold, silver, oil, corn, wheat, and rice trading in U.S. markets. The findings suggested the existence of positive equicorrelation between commodity futures market returns and this impact was found to be stronger during periods of economic downturns and financial turbulence. Moreover, they compared optimal portfolio weights and hedge ratios and assigned higher values for the hedge ratios during

periods of crises which may influence portfolio trading strategies and investment decisions.

Chhimwal, Bapat, and McMillan (2020) used autoregressive moving average (ARMA) and threshold GARCH (TGARCH) models to estimate the effect of both domestic and foreign investment flows on the volatility of stocks trading in Indian markets. The results indicated that foreign investment flows have a positive impact on market volatility but this effect is reduced when domestic investment flows are taken into account. This impact may assist portfolio managers in developing successful volatility strategies in order to optimize returns.

A number of studies have explored these issues examining various European markets. Corbet and Twomey (2015) investigated the Irish debt crisis. They found evidence of the so-called contagion effect that is an unusually high correlation between the Irish and several European equity markets, during the Irish financial crisis. Gjika and Horváth (2013) found that the correlations among stock markets in Central Europe and between Central Europe *vis-à-vis* the Euro area remained at high levels during the financial crisis. Dajcman and Festic (2012) showed that the global financial crisis of 2007-2008, had a major impact on the increased co-movement of the Slovenian stock market with European stock markets. Dajcman, Festic, and Kavkler (2012) examined the dynamics of the United Kingdom, Germany, France, and Austria stock markets. They concluded that the global financial crisis of 2007-2008 only slightly and temporarily increased the already high level of co-movement between these European stock markets. Denkowska and Wanat (2020) investigated the weekly return rates of eight insurance companies (five from Europe and the biggest insurers from the USA, Canada, and China) during the period 2005 to 2018. They concluded that all the considered insurance companies are positively correlated and this correlation is stronger in times of turbulences. Finally, Tevdovski and Stojkoski (2021) discovered that there are strong persistence effects and significant linkages between South-Eastern European stock markets.

In addition to GARCH, a variety of alternative volatility models have been applied in the literature, namely, implied volatility, realized volatility, range-based volatility, and stochastic volatility (Danielson, 2011).

3. DATA

Figure 1 below, graphs daily values of the Athens General Index from January 2, 2006, to August 25, 2017. All data are collected from the Athens Stock Exchange database and sectors' index values are those reported by the Stock Exchange.

The market sectors selected were industry-services, emporium, construction, petroleum, telecommunications, food-beverages and banks as reported and categorized by the Athens Stock Exchange. The examined period was limited to January 2006 until August 2017 due to the restricted availability of data.

From Figure 1 we observe four major downward trending periods (shown by the solid ellipses in the graph): 1) from the end of 2007 until

early 2009; 2) end 2009 until mid-2010; 3) early 2011 until mid-2012; and 4) mid-2014 until early 2016. The first downward trend was caused by the global financial and economic crisis of 2007-2008. The second drop was brought about by the Greek government-debt crisis which resulted in the imposition of very strict rules and monitoring of the Greek economy by the country's international lenders (EU and the IMF). The foreign supervision

and very stringent monitoring of the Greek government's budget cuts in addition to the severe austerity measures introduced and implemented, accentuated the third distinct decline period in our study. Finally, the fourth dip in Greek stock prices was provoked by the enforcement of severe capital controls wreaked upon the Greek banks, as a result of the Greek referendum on remaining in the Eurozone (July 2015).

Figure 1. Athens Stock Index

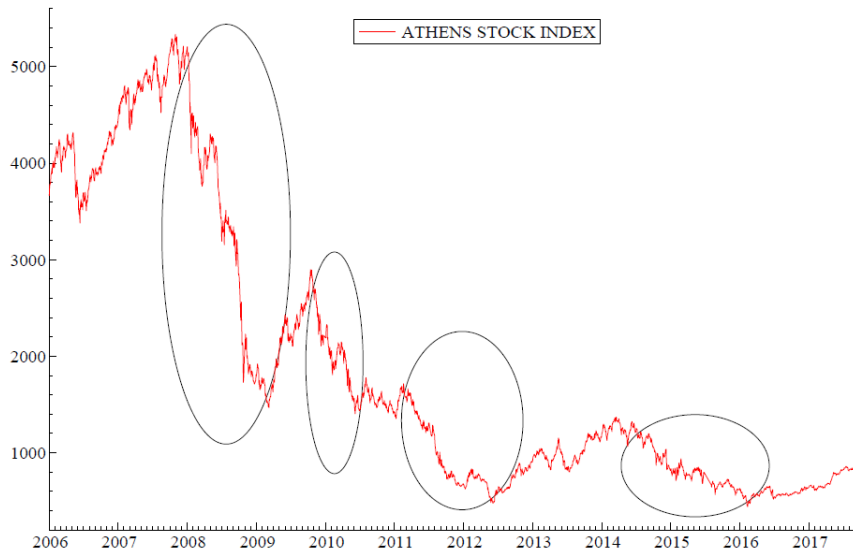
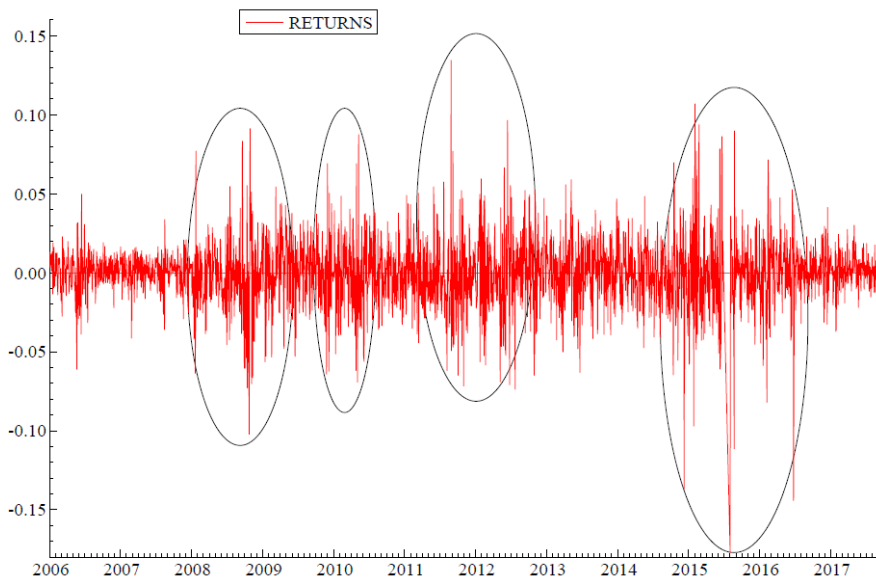


Figure 2 illustrates the graph of log returns of the Athens Stock Exchange Index.

increases during periods of crisis (volatility is greatly inflamed during sharp drops in share prices).

As can be observed by the solid ellipses in the graph, the volatility of the Greek stock market

Figure 2. Log returns of the Athens Stock Index



Figures 3 and 4 next, present histograms and descriptive statistics for the Stock Index and its log returns.

its values. The same information is also revealed from the positive value of the skewness coefficient. Furthermore, the probability value of the Jarque-Bera test fails to accept the null hypothesis of normality.

The histogram of the Stock Index in Figure 3 shows an asymmetric (right-skewed) distribution for

Figure 3. Histogram-statistics of Athens Stock Index

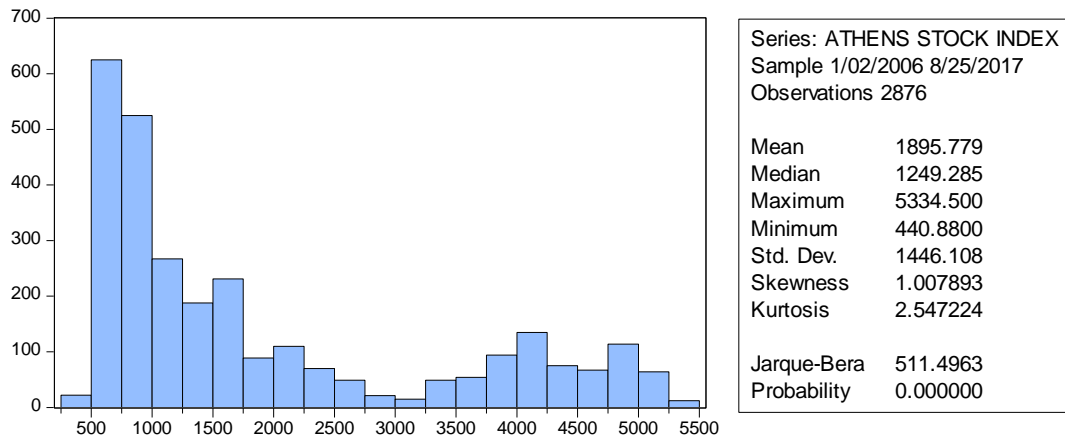
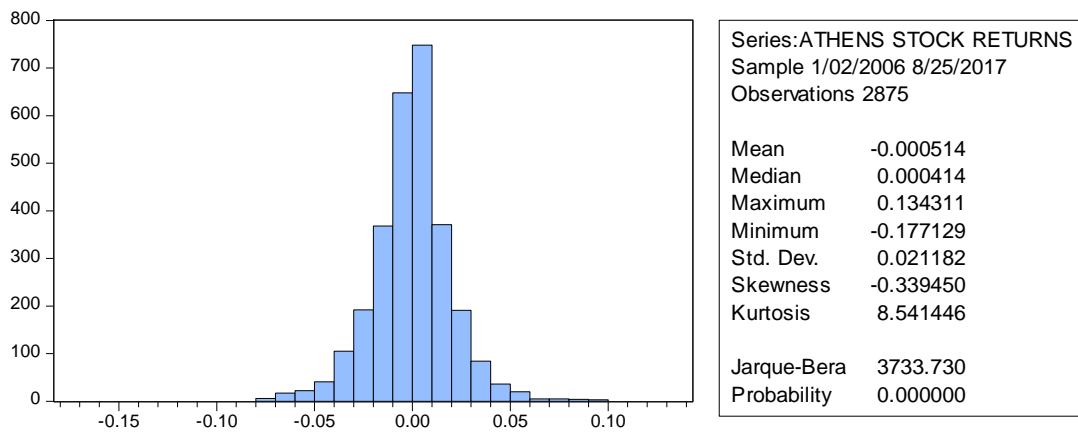


Figure 4, below, shows a slightly left-skewed distribution for the log returns of the Athens Stock Index. Figure 4, depicts the distribution of returns. This distribution is leptokurtic since the value of the kurtosis coefficient is greater than 3 (8.5414).

This finding hints at a “fat-tailed” distribution, which in turn, indicates the possibility of incurring extreme losses. Furthermore, the probability value of the Jarque-Bera test (3733.73) shows that the distribution of returns is not normal.

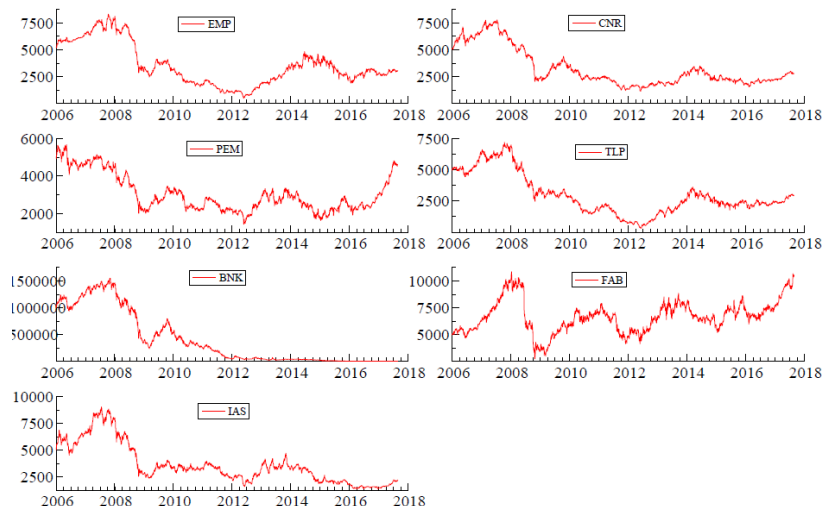
Figure 4. Histogram-statistics of Log returns



The graphs in Figure 5, below, depict daily values from January 2, 2006, to August 25, 2017, of seven Greek sectors: industry and services (IAS),

emporium (EMP), construction (CNR), petroleum (PEM), telecommunications (TLP), food and beverages (FAB) and banks (BNK).

Figure 5. Seven Greek sectors' indices



The banking sector (BNK) demonstrates the worst performance among all seven sectors included in this study. Banks' share prices have been sharply falling from the end of 2007 until the beginning of 2012 and this decline has bottomed out since then. This is mainly due to the severe economic crisis caused by the Greek debt debacle that destroyed banks' balance sheets. The industry and services sector (IAS) shows a sharp drop from the end of 2007 until the end of 2009, followed by two upward trend periods (2009-2012 and 2012-2016) with share prices remaining stagnant since then. The food and beverages sector (FAB) share prices after an initial sharp decline period that lasted 18 months have been intermittently

increasing during the later years investigated in this study. The petroleum (PEM) and telecommunication (TLP) sectors behaved similarly, firstly decreasing until the beginning of 2012 and then rising in the remaining five year time period. The construction sector (CNR) exhibits a steady fall until the end of 2012 and since the beginning of 2013 share prices have been hovering around that level. Finally, the emporium sector (EMP) demonstrates two widespread protracted trends, one downward (end 2007-beginning 2012) and one upward (beginning 2012-August 2017).

The graph of log returns for the seven sectors is presented next in Figure 6.

Figure 6. Log returns of seven Greek sectors

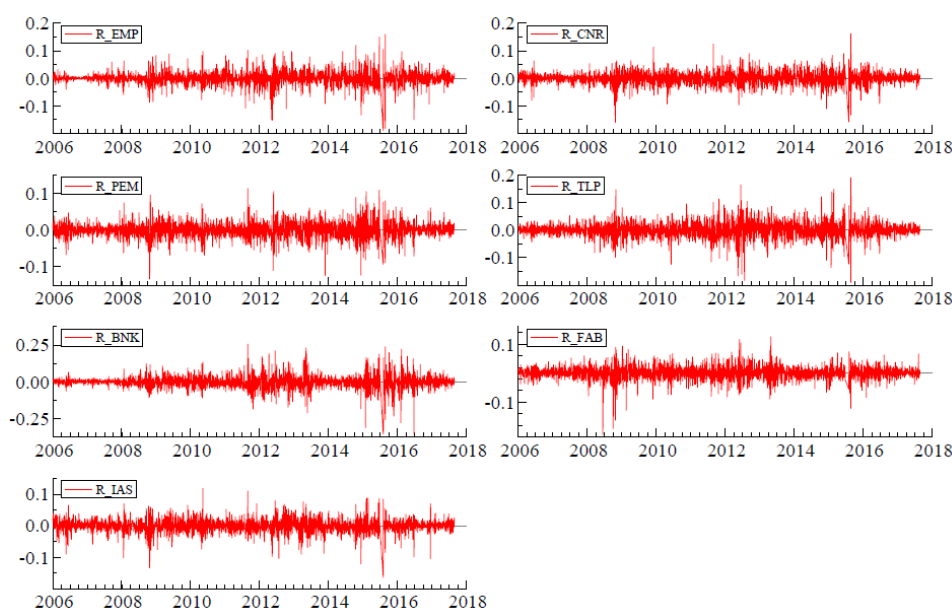


Table 1. Descriptive statistics

	EMP	CNR	PEM	TLP	BNK	FAB	IAS
Mean	3551.511	3246.050	3055.899	2966.676	400119.4	6655.917	3643.474
Median	3048.985	2436.615	2735.665	2488.320	96016.00	6630.375	3259.060
Maximum	8328.090	7794.370	5680.390	7202.490	1551614.	10869.02	9028.340
Minimum	475.5500	1141.830	1429.410	311.0400	431.4000	2728.020	1365.790
Std. Dev.	1938.573	1751.303	987.5555	1628.354	490926.5	1490.366	1864.523
Skewness	0.713172	1.151502	0.859389	0.840145	0.996669	0.295539	1.112566
Kurtosis	2.468029	2.978696	2.559697	2.848353	2.451919	3.055260	3.368517
Jarque-Bera	277.7079	635.6299	377.2434	341.0904	512.1423	42.23247	609.5940
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	R_EMP	R_CNR	R_PEM	R_TLP	R_BNK	R_FAB	R_IAS
Mean	-0.000182	-0.000204	-2.33E-05	-0.000180	-0.002375	0.000262	-0.000283
Median	-3.15E-05	0.000172	0.000349	0.000000	-0.001231	0.000350	5.57E-05
Maximum	0.159140	0.162091	0.112899	0.189757	0.255593	0.125437	0.118114
Minimum	-0.189236	-0.159900	-0.132987	-0.189757	-0.355596	-0.211129	-0.163852
Std. Dev.	0.024719	0.023083	0.021460	0.028470	0.045403	0.023132	0.021665
Skewness	-0.236206	-0.222871	-0.112142	-0.100327	-0.573689	-0.595302	-0.414923
Kurtosis	9.942929	7.371977	6.350135	7.859247	11.91517	9.851193	7.177681
Jarque-Bera	5801.204	2313.521	1350.496	2833.378	9678.782	5792.692	2173.220
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

The results of Table 1 indicate that there exist "fat-tailed" negatively skewed distributions throughout our sample. The skewness coefficients depicted in Table 1 take positive values for all seven sectors also suggest an asymmetric distribution. The kurtosis coefficients again suggest the existence of fat-tailed distributions. Moreover, the probability

values of the Jarque-Bera test again reject the hypothesis of normality.

A time-series process is weakly stationary if the mean, variance, and covariance of the process do not change by time shifts. Weak stationarity is also called covariance stationary. That is, the mean and the variance are unchanged through time and the covariance between two observations depends

only on the “time distance” between them. In other words, a weak stationary random variable is used to assume that distributional measures such as mean, variance, and covariance are not time-dependent. However, other distributional characteristics of the process like skewness, kurtosis, etc. do not have that property of time invariance.

We examine the stationary properties of the seven-time series by using the well-known Augmented Dickey-Fuller (ADF) test.

The null hypothesis of the test assumes that the variable has at least one unit root (it is nonstationary). The alternative hypothesis of the test is that of stationarity. The ADF tests are given in Table 2.

Table 2. ADF tests

	ADF	p-value
EMP	-1.276554	0.642595
CNR	-1.482115	0.542791
PEM	-1.854822	0.354117
TLP	-1.448171	0.559901
BNK	-1.238333	0.659893
FAB	-1.851751	0.355599
IAS	-1.618957	0.472709
R_EMP	-23.93318	6.05E-49
R_CNR	-27.57038	2.37E-47
R_PEM	-29.43117	8.57E-45
R_TLP	-17.92800	1.29E-41
R_BNK	-12.93479	3.51E-28
R_FAB	-11.41081	2.08E-23
R_IAS	-11.46543	1.40E-23

The results of the ADF tests indicate that the time series of returns are stationary.

4. RESEARCH METHODOLOGY

In this section, we discuss the specification of the DECO-MGARCH (Engle & Kelly, 2012), which is closed related to DCC-MGARCH (Engle, 2002). The DECO-MGARCH is used to obtain estimates of the time-dependent correlations (equicorrelation) among the seven sectors.

Given the returns $r_{i,t}$ of each sector $i = I, K, N$ at time $t = I, K, N$, the VAR(1)-MGARCH(1,1) model consists of the following set of equations:

$$r_{i,t} = \varphi_{0,i} + \varphi_{1,i}r_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

$$\varepsilon_{i,t} = \sigma_{i,t}z_{i,t} \tag{2}$$

Table 3. Estimates of VAR(1)-MGARCH(1,1) for returns of the seven sectors

	$\varphi_0 \times 10^4$	φ_1	$\delta \times 10^4$	α	β
R_EMP	5.92 (2.36)	0.088 (4.04)	0.002 (0.94)	0.107 (5.14)	0.908 (57.7)
R_CNR	5.95 (1.51)	0.010 (0.49)	0.062 (2.06)	0.092 (4.29)	0.902 (38.7)
R_PEM	5.42 (1.58)	0.024 (1.13)	0.073 (2.75)	0.090 (6.28)	0.897 (54.6)
R_TLP	4.34 (1.07)	0.025 (1.21)	0.032 (1.76)	0.071 (5.14)	0.928 (66.6)
R_BNK	5.40 (1.04)	0.076 (3.33)	0.030 (1.65)	0.121 (5.40)	0.891 (50.2)
R_FAB	9.57 (2.69)	-0.062 (-2.74)	0.103 (0.92)	0.067 (1.86)	0.916 (16.9)
R_IAS	4.35 (1.13)	0.089 (4.02)	0.121 (3.25)	0.139 (6.39)	0.847 (40.5)

Note: t-statistics are in parentheses.

The empirical results show very persistent volatility for all sectors.

The equicorrelation among with Athens Stock Index values is presented in Figure 7.

The correlation of the seven sectors is positive for the whole sample indicating that all sectors were

where, σ and z are the conditional volatility and standardized residual respectively.

The Gaussian assumption cannot explain the leptokurtosis of the stock returns.

For this purpose, we replace the normal distribution with the student’s t-distribution as suggested by Bollerslev (1987). For each i the distribution of the error term is:

$$f(\varepsilon_t) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu+1}{2}\right)} \left(1 + \frac{\varepsilon_t^2}{\nu}\right)^{-\frac{\nu+1}{2}} \tag{3}$$

where, ν is the degree of freedom of the t-distribution.

The dynamics of the volatility is given by the MGARCH(1,1) model:

$$\sigma_{i,t}^2 = \delta_i + \alpha_i\varepsilon_{i,t-1}^2 + \beta_i\sigma_{i,t-1}^2 \tag{4}$$

The conditions: $\delta \geq 0, \alpha \geq 0, \beta \geq 0$, and $\alpha + \beta < 1$, in equation (4) guarantee the positive values for the estimates of the conditional variance.

The closer $\alpha + \beta$ is to one the higher the persistence of volatility is.

For each time t , the correlation among the seven sectors’ returns is given by the $N \times N$ equicorrelation matrix R_t :

$$R_t = (1 - \rho_t)I + \rho_tJ \tag{5}$$

where, J is an $N \times N$ matrix of ones, I is an $N -$ dimensional unit matrix and the equicorrelation coefficient ρ_t is obtained from the equations:

$$\rho_t = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \dots, i, j = 1, \dots, N \tag{6}$$

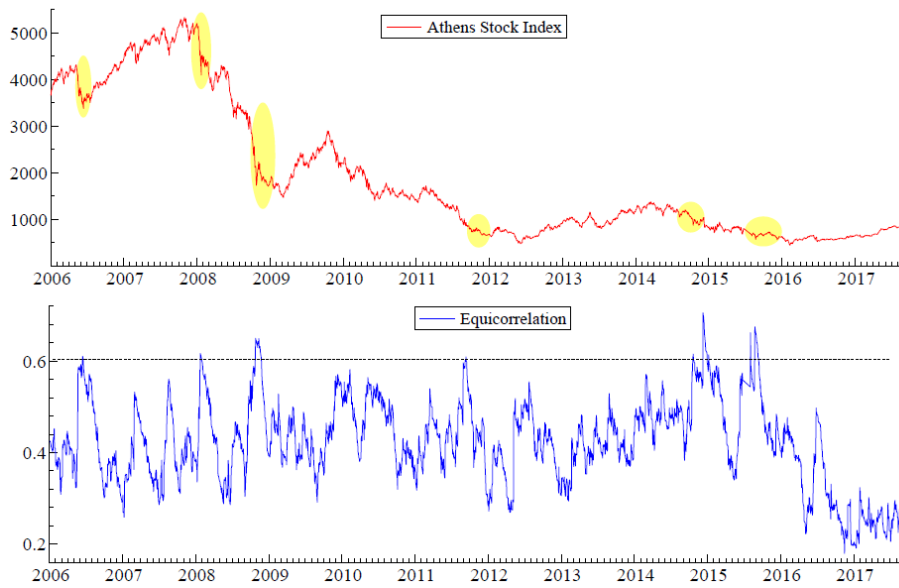
where, $q_{ij,t}$ is the i, j element of the variance-covariance matrix of the residuals (for detailed explanation see Engle and Kelly, 2012, p. 215).

5. RESULTS AND DISCUSSION

The estimation of the VAR(1)-MGARCH(1,1) model is presented in Table 3 below.

moving in the same direction. From the equicorrelation graph, we spotted high correlations as those exceeding the 0.6 value. Then we confirm that these high correlations correspond to various price-falling periods (crises) of the stock market (shaded areas in the top graph of Figure 7).

Figure 7. Athens Stock Index and equicorrelation



To summarize, the estimated values of the dynamic correlations among the seven sectors verify that the correlations were high especially in crisis periods of the stock market.

The entropy of a random variable is the average level of “information” or “uncertainty” in the variable’s possible outcomes. If an outcome is very probable it is no surprise and therefore uninteresting when that outcome occurs as expected (very low uncertainty). However, if an outcome or event is unlikely to occur it is much more informative to learn that the outcome actually happened or will happen. The information content of an outcome or event is a function that decreases as the probability of that outcome increases. Thus, entropy measures the expected (i.e., average or rate) information revealed by the outcome of a random trial. Entropy is an index of complexity or uncertainty for a given time series. Large entropic values are associated with higher uncertainty or complexity.

To examine the evolution of Greek stock market participants’ expectations during the period 2006–2017, we calculate time-dependent entropy by using the equicorrelation values. Specifically, we estimate the sample entropy suggested by Pincus (1991). Pincus (1991) developed a mathematical framework of formulas and statistics to calculate entropy measures in order to quantify the concept of randomness or uncertainty. He found that stochastic processes for which successive terms are correlated can produce finite dimension values. Pincus calculated sample entropy is a distribution-free statistic that is insensitive to outliers. Greater sample entropy values consort with an increase in randomness (uncertainty).

The estimation of the sample entropy is discussed below.

Let x define time series of n points, that is $x = \{x_1, \dots, x_n\}$.

For the time series x any vector of m points ($m < n$), starting at the i -th term is given by:

$$x_m(i) = \{x_i, x_{i+1}, \dots, x_{i+m-1}\} \quad (7)$$

The distance of two vectors $x_m(i)$ and $x_m(j)$ length m is defined as:

$$d(x_m(i), x_m(j)) = \max\{|x_{i+k} - x_{j+k}| : 0 \leq k \leq m - 1\} \quad (8)$$

Two vectors $x_m(i)$ and $x_m(j)$ are similar to each other if their distance is at most r (for some $r > 0$), that is:

$$d(x_m(i), x_m(j)) \leq r \quad (9)$$

Let B_i denotes the number of vectors $x_m(j)$ similar to $x_m(i)$ and A_i the number of vectors $x_{m+1}(j)$ similar to $x_{m+1}(i)$ for a fixed i and m .

For time series x the (average) number of vectors $x_m(j)$, $j \neq i, \dots, n - m$, that are similar to $x_m(i)$ within a tolerance level $r > 0$, is defined as:

$$B_i^m(r) = \frac{B_i}{n - (m - 1)} \quad (10)$$

Then the probability the two sequences will match for m points is given by the equation:

$$B^m(r) = \frac{1}{n - m} \sum_{i=1}^{n-m} B_i^m(r) \quad (11)$$

Similarly, given time series x , the (average) number of vectors $x_{m+1}(j)$, $j \neq i = 1, \dots, n - m$, that are similar to $x_{m+1}(i)$ within a tolerance level $r > 0$, is defined as:

$$A_i^m(r) = \frac{A_i}{n - (m - 1)} \quad (12)$$

The probability the two sequences will match for $m + 1$ points is given by the equation:

$$A^m(r) = \frac{1}{n - m} \sum_{i=1}^{n-m} A_i^m(r) \quad (13)$$

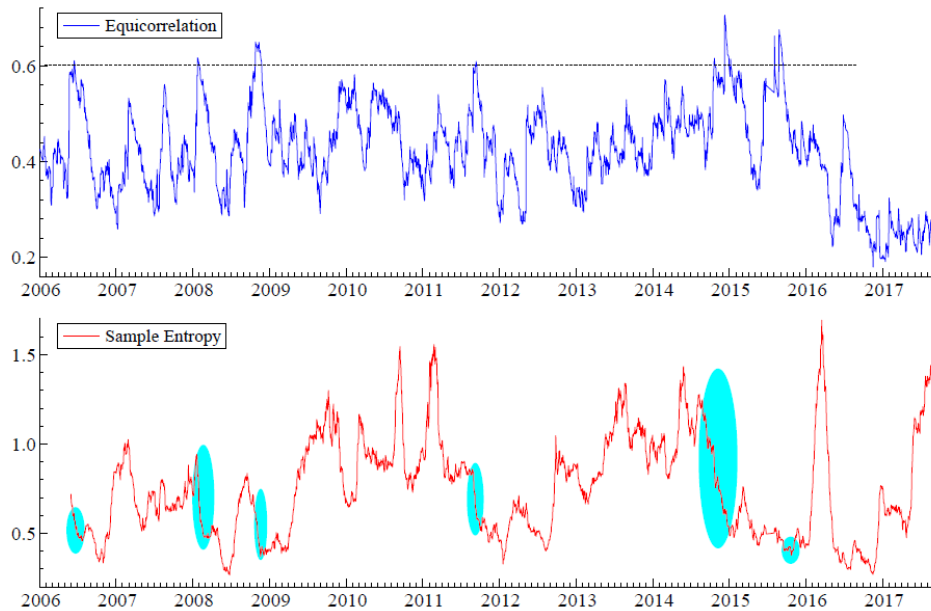
From equations (11) and (13), the sample entropy, SE , is defined:

$$SE(m, r, n) = -\ln\left(\frac{A^m(r)}{B^m(r)}\right) \quad (14)$$

Using a moving window we calculated the sample entropy through time. In the paper, we set 100 observations for the length of moving window (n), $m = 2$ and tolerance $r = 0.2 \times s$, where s is the standard deviation of the time series.

The equicorrelation among with sample entropic values is presented in Figure 8.

Figure 8. Equicorrelation and sample entropy



Sample entropy values are shown in the bottom graph of Figure 8. The shaded areas of the sample entropy graph correspond to time periods of the high correlation of returns among the seven sectors. The graph clearly shows that the sample entropy exhibits a downward trending for all these periods. This shows that expectations of market participants in the seven sectors become less dispersed during periods of crisis (high correlation of returns). These findings are in line with Bracker and Koch (1999) who found that volatility is positively related to the magnitude of correlations and Yang (2005) who suggests that correlations increase during periods of high market volatility.

6. CONCLUSION

This paper tried to analyze the dynamic behavior of seven Athens Stock Exchange sectors (markets) using daily observations from January 2006 to August 2017 by employing a dynamic equicorrelation multivariate GARCH model (DECO-MGARCH). Furthermore, we used time-dependent entropic measures to examine empirically the uncertainty (expectations) regarding the correlation behavior of these seven sectors. This paper is unique in that most studies in this field concentrate on developed markets, with only a few examining developing and emerging markets, and none of them using entropy measures to quantify correlations between sectors' indices.

The empirical results provide evidence supporting the view of high correlations during periods of crises. Our findings are in line with Tsai and Chen (2010) and Garnaut (1998) who reported

evidence suggesting that crises resulted in significant short-term increases in correlation. Furthermore, Schwebach et al. (2002), Cho and Parhizgari (2008) and Medo et al. (2009) reported similar results for a number of developing markets. In addition, dynamic entropy measures indicate that the expectations of market participants were more concentrated (less spread out) during periods of crises. We found evidence showing very persistent volatility for all sectors. The assertion that correlation increases during times of high market volatility are very well documented in the literature (Karolyi & Stulz, 1996; Ramchand & Susmel, 1998; Longin & Solnik, 2001; etc.). Moreover, the probability values of the Jarque-Bera test again reject the hypothesis of normality. To summarize, the estimated values of the dynamic correlations among the seven sectors verify that the correlations were high especially in crisis periods. These results appear to conform to the contention that investors may gain lower benefits from diversification during crisis periods.

Therefore, our findings support the view that market participants share the same opinions (entropy exhibits low uncertainty) during crises and hence are acting accordingly (exhibiting high correlation), confirming previous studies (Cao et al., 2013; Meric et al., 2008).

The findings of this study could be of interest to investors and portfolio managers who want to learn more about stock market volatility and correlations and assist them in better understanding stock market dynamics and making better investment decisions and build new diversification strategies during times of financial uncertainty.

This research can be expanded in a number of ways. It would be beneficial to look into volatility and correlation in commodities markets and futures markets for both stocks and commodities. Second, it may be useful to investigate the volatility and spillover effects among different market sectors,

among different stocks, and among futures markets. Moreover, it might be worthwhile to examine different and longer time periods and canvass market uncertainty and trends in more developing countries.

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