Proceedings of the 2005 International Conference on Simulation and Modelling
V. Kachitvichyanakul, U. Purintrapiban, and P. Uthayopas, eds.

MODELLING RISK SPILLOVERS IN ENVIRONMENTAL FINANCE

Suhejla Hoti

School of Economics and Commerce
University of Western Australia

Michael McAleer

School of Economics and Commerce
University of Western Australia

Laurent L. Pauwels

Economics Section
Graduate Institute of International Studies, Geneva

ABSTRACT

Environmental issues have become increasingly important in economic research and policy for sustainable development. Such issues are tracked by the Dow Jones Sustainable Indexes (DJSI) through financial market indexes that are derived from the Dow Jones Global Indexes. The environmental sustainability activities of firms are assessed using criteria in three areas, namely economic, environmental and social. Risk (or uncertainty) is analysed empirically through the use of conditional volatility models of investment in sustainability-driven firms that are selected through the DJSI. This paper analyses the trends and volatility in DJSI indexes using daily data from 31 December 1998 to 1 March 2004. The conditional variance of the DJSI indexes is analysed using three multivariate GARCH models, namely CCC, VARMA-GARCH and VARMA-AGARCH. These models are able to capture the dynamics in the conditional variance and the existence of risk spillovers in the DJSI indexes.

1. INTRODUCTION

Environmental sustainability involves the economic and financial behaviour of agents and firms in the private sector, and policy making and implementation. The sustainable economic behaviour by firms encourages investors to diversify their financial portfolios and to invest in "sustainable" companies.

The Dow Jones Sustainability Indexes (DJSI) are part of a family of financial indexes that are derived in the same manner as the more well-known financial market indexes, such as the Dow Jones Industrial Average (DJIA) and the STOXX index. The DJSI is based on a selection of leading firms that take environmental and social issues seriously in their business practices (for further details see Hoti, McAleer and Pauwels (2005a,b)).

In this paper, we analyse empirically the time-varying conditional variance (or risk) associated with investing in leading sustainability-driven firms using multivariate models of conditional volatility. As the concept of environmental risk has had several different interpretations in the economics literature, we use the definition given in Hoti, McAleer and Pauwels (2005a):

> *"Environmental risk is the volatility associated with the returns to a variety of environmental sustainability indexes."*

Models of the conditional variance, or risk, of a time series have long been popular in the financial econometrics literature. Three of the most popular models to capture the time-varying volatility in financial time series are the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model of Engle (1982) and Bollerslev (1986), the GJR model of Glosten, Jagannathan and Runkle (1992), and the Exponential GARCH (EGARCH) model of Nelson (1991). Multivariate extensions of GARCH models are also available in the literature, such as the Constant Conditional Correlation (CCC) GARCH model Bollerslev (1990), Vector Autoregressive Moving Average GARCH (VARMA-GARCH) model of Ling and McAleer (2003), and VARMA Asymmetric GARCH (VARMA-AGARCH) model of Hoti, Chan and McAleer (2002).

To date there seem to have been only a few empirical studies of such sustainability indexes. It is only recently that time-varying models of heteroscedasticity have been applied to sustainability indexes (see Hoti, McAleer and Pauwels (2005a)).

The plan of the paper is as follows. Section 2 presents the Dow Jones Sustanability Indexes and discusses the key features of the various indexes. Univariate conditional volatility models for daily observations on the sustainability indexes are presented in Section 3. The data are described in Section 4, and the empirical results for the multivariate models are analysed in Section 5. Some concluding remarks are given in Section 6.

2. DOW JONES SUSTAINABILITY INDEXES (DJSI)

Dow Jones Sustainability Indexes (DJSI) commenced in 1998, and report on the financial performance of leading sustainability-driven firms worldwide (for a discussion of the DJSI indexes, see Hoti, McAleer and Pauwels (2005a,b)). These sustainability indexes were created by the Dow Jones Indexes, STOXX Limited and the SAM group.

The main purpose of the DJSI is to provide asset managers with a benchmark to manage sustainability portfolios, and develop financial products and services that are linked to sustainable economic, environmental and social criteria. DJSI indexes quantify the development and promotion of sustainable values on the environment and society by the business community. They also enable the promotion of sustainability within the private sector by informing investors about firms that behave in an environmentally sustainable manner.

As for the Dow Jones Global Indexes, the DJSI features the same methods for calculating, reviewing and publishing data. The DJSI is used in 14 countries, with 50 licenses having been sold to asset managers. There are two sets of DJSI indexes, namely the DJSI World and the DJSI STOXX (which is a pan-European index). The latter index is also subdivided into another regional index, namely DJSI EURO STOXX, which accounts solely for Euro-zone countries.

Dow Jones Sustainability World Indexes (DJSI World) is constructed by selecting the leading 10% of sustainability firms (which number more than 300) in the Dow Jones Global Index, which covers 59 industries over 34 countries. The composite DJSI World is available in four specialised subset indexes, which exclude companies that generate revenue from (1) tobacco, (2) gambling, (3) armaments or firearms, and (4) alcohol, in addition to the three previously mentioned items.

Two regional indexes, the DJSI STOXX and DJSI EURO STOXX, were first published on 15 October 2001. They include 179 components and record the financial performance of the leading 20% of European sustainability companies chosen from the Dow Jones STOXX 600. Moreover, two specialised indexes are made available for both regional composite indexes, which corresponds to category (4) given above.

The DJSI World and DJSI STOXX are reviewed annually and quarterly to ensure consistency. They also accommodate potential changes in the behaviour and status of companies which could affect their sustainability performance (such as bankruptcies, mergers and takeovers). Both indexes comprise companies from 60 industry groups and 18 market sectors.

3. MULTIVARIATE MODELS OF CONDITIONAL VOLATILITY FOR SUSTAINABILITY INDEXES

The primary empirical purpose of the paper is to model the DJSI indexes and their associated volatility for the period 31 December 1998 to 1 March 2004. This approach is based on Engle’s (1982) development of time-varying volatility (or uncertainty) using the autoregressive conditional heteroskedasticity (ARCH) model, and subsequent developments associated with the ARCH family of models (see, for example, the recent survey by Li, Ling and McAleer (2002)). Of the wide range of univariate conditional volatility models, the two most popular have been the symmetric generalised ARCH (GARCH) model of Bollerslev (1986) and the asymmetric GARCH (or GJR) model of Glosten, Jagannathan and Runkle (1992), especially for the analysis of financial data. Several other theoretical developments have recently been suggested by Wong and Li (1997), Hoti, Chan and McAleer (2002), Ling and McAleer (2002a,b) and Ling and McAleer (2003). A comparison of the structural and statistical properties of alternative univariate and multivariate conditional and stochastic volatility models is given in McAleer (2005).

Three constant conditional correlation models, namely the no-spillover CCC model of Bollerslev (1990), the symmetric VARMA-GARCH model of Ling and McAleer (2003), and the asymmetric VARMA-GARCH (or VARMA-AGARCH) model of Hoti, Chan and McAleer (2002), are estimated using daily data on DJSI and financial indexes. The VARMA-AGARCH model includes the CCC and VARMA-GARCH as special cases.

Consider the following specification for the return on a stock index or on a financial asset (as measured in log-differences), y_t:

$$
\begin{aligned}
y_t &= E\left(y_t \mid \Im_{t-1}\right) + \varepsilon_t, \qquad t = 1,\dots,n \\
\varepsilon_t &= D_t \eta_t
\end{aligned}
\tag{1}
$$

where $\Im_t$ is the information set available to time *t*, $y_t = (y_{1t},\dots,y_{mt})'$ measures returns for different indexes,

$\eta_t = (\eta_{1t},...,\eta_{mt})'$ is a sequence of independently and identically distributed random vectors that is obtained from standardising the shocks to index returs, ε_t, using the standardisation $D_t = diag(h_{1t}^{1/2},...,h_{mt}^{1/2})$, $m\,(=4)$ is the number of index returns, and $t = 1,...,1357$ (for DJSI STOXX and DJSI EURO STOXX) and $t = 1,...,1371$ (for DJIA and S&P500) daily observations for the period 31 December 1998 to 1 March 2004.

The CCC model assumes that the conditional variance of the shocks to index return i, $i = 1,...,m$, follows a univariate GARCH(r,s) process, that is,

$$h_{it} = \omega_i + \sum_{l=1}^{r} \alpha_{il}\varepsilon_{it-l}^2 + \sum_{l=1}^{s} \beta_{il} h_{it-l} \tag{2}$$

where α_{il} represents the ARCH effects, or the short run persistence of shocks to index return i, and β_{il} represents the GARCH effects, or the contribution of such shocks to long run persistence. This model assumes the independence of conditional variances, and hence no spillovers in volatility, across different index returns. Moreover, CCC does not accommodate the (possibly) asymmetric effects of positive and negative shocks on conditional volatility. It is important to note that $\Gamma = \{\rho_{ij}\}$ is the matrix of constant conditional correlations, in which $\rho_{ij} = \rho_{ji}$ for $i, j = 1,...,m.$ Therefore, the multivariate effects are determined solely through the constant conditional correlation matrix.

Equation (2) assumes that a positive shock ($\varepsilon_t > 0$) has the same impact on the conditional variance, h_t, as a negative shock ($\varepsilon_t < 0$), but this assumption is often violated in practice. An extension of (2) to accommodate the possible differential impact on the conditional variance between positive and negative shocks is given by

$$h_{it} = \omega_i + \left(\sum_{l=1}^{r} \alpha_{il} + \sum_{l=1}^{r} \gamma_{il} I\left(\eta_{it-l}\right)\right)\varepsilon_{it-l}^2 + \sum_{l=1}^{s} \beta_{il} h_{it-l} \tag{3}$$

in which $\varepsilon_{it} = \eta_{it}\sqrt{h_{it}}$ for all i and t, and $I\left(\eta_{it}\right)$ is an indicator variable such that

$$I\left(\eta_{it}\right) = \begin{cases} 1, & \varepsilon_{it} < 0 \\ 0, & \varepsilon_{it} > 0\ . \end{cases}$$

As in (1), $\eta_t = \left(\eta_{1t},...,\eta_{mt}\right)'$ is a sequence of *iid* random vectors, with zero mean and covariance matrix Γ, so that $\varepsilon_t = D_t\eta_t$, in which D_t depends only on $H_t = \left(h_{1t},...,h_{mt}\right)'$.

As an extension of (3) to incorporate multivariate effects across equations, and hence spillovers in volatility across different index returns, it is necessary to define h_{it} to contain past information from ε_{it}, ε_{jt}, h_{it} and h_{jt} for $i, j = 1,...,m$, $i \neq j$. Thus, the asymmetric VARMA(*p*,*q*)-GARCH(*r*,*s*), or VARMA-AGARCH, model of Hoti, Chan and McAleer (2002) is defined as follows:

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t \tag{4}$$

$$\varepsilon_t = D_t\eta_t$$
$$H_t = W + \left(\sum_{l=1}^{r} A_l + \sum_{l=1}^{r} C_l I(\eta_{t-1})\right)\vec{\varepsilon}_t + \sum_{l=1}^{p} B_l H_{t-l} \tag{5}$$

where $D_t = diag(h_{1t}^{1/2},...,h_{mt}^{1/2})$, A_l, C_l and B_l are matrices with typical elements α_{ij}, γ_{ij} and β_{ij}, respectively, for $i, j = 1,...,m$, $I\left(\eta_t\right) = diag\left(I\left(\eta_{1t}\right),...,I\left(\eta_{mt}\right)\right)$ is an $m \times m$ matrix, $\Phi\left(L\right) = I_m - \Phi_1 L - ... - \Phi_p L^p$ and $\Psi\left(L\right) = I_m - \Psi_1 L - ... - \Psi_p L^p$ are polynomials in L, I_k is the $k \times k$ identity matrix, and $\vec{\varepsilon}_t = \left(\varepsilon_{1t}^2,...,\varepsilon_{mt}^2\right)'$.

The univariate constant-mean GJR model is obtained from (4)-(5) either by setting $m = 1$ and $\Phi(L) = \Psi(L) = 1$, or by specifying A_l, C_l and B_l as diagonal matrices. The CCC model (1)-(2) is obtained from (4)-(5) by setting $A_l = diag\{\alpha_{il}\}$, $B_l = diag\{\beta_{il}\}$ and $C_l = 0$ for $l = 1,...,r$, while the VARMA-GARCH model is obtained from (4)-(5) by setting $C_l = 0$ for $l = 1,...,r$.

4. DATA DESCRIPTION

The DJSI World, DJSI STOXX, and DJSI EURO STOXX are available on both a daily and monthly basis from the Dow Jones Sustainability Indexes website (see http://www.sustainability-indexes.com). All the indexes are calculated as the returns on the index, in both USD and EURO currencies. In this paper, we estimate models using only the daily data on the index denominated in USD, as daily data are more informative with regard to the existence of volatility.

As the DJSI World index is calculated on a 7-day per week basis, whereas the STOXX indexes are calculated on a 5-day per week basis, only the two STOXX indexes are considered in this paper. We also analyse two prominent financial indexes, namely the Dow Jones Industrial Average (DJIA) and Standard & Poor's 500 (S&P500), which are also calculated on a 5-day per week basis.

The empirical analysis in this paper involves two DJSI indexes and two financial indexes for the period 31/12/1998 to 1/04/2004. Until 29/12/2000, all four indexes were reported consistently. However, starting from 1/01/2001, observations for both DJSI STOXX and DJSI EURO STOXX indexes are frequently missing, and in many cases the reported dates are the same for two consecutive observations. This does not seem to be the case for the DJIA and S&P500 indexes. As a result, there are 1357 and 1371 daily observations for the DJSI indexes and the financial indexes, respectively, for the period 31 December 1998 to 1 March 2004.

Levels and returns for each of the four indexes, namely DJSI STOXX, DJSI EURO, DJIA and S&P500, are presented in Figure 1-2. Apart from DJIA, the patterns in both series are remarkably similar. There is a substantial clustering of returns for each series, with only the DJIA returns showing any differences from the remaining three series.

5. EMPIRICAL RESULTS

As shown in Figures 3-4, there is substantial volatility in each of the four series. Using the data on the daily indexes, the conditional mean is modelled in each case as an AR(1) process. Table 1 provides the ADF and Phillips-Perron (PP) unit root tests for the four indexes, as well as their log-differences (or rates of return). It is clear that the indexes are non-stationary, while their rates of return are stationary.

In addition to estimating the conditional mean for each index, the CCC, VARMA-GARCH and VARMA-AGARCH models are used to estimate the conditional volatility associated with the two types of indexes. On the basis of the univariate standardised index return shocks obtained from the CCC model, the three multivariate models are used to estimate the conditional correlation coefficients of the daily index return shocks between the DJSI indexes and financial indexes, respectively. This can provide useful information regarding the relationship between the indexes, in each category, in terms of the shocks to index returns.

In this paper, the estimates of the parameters are obtained using the Berndt, Hall, Hall and Hausman (BHHH) (1974) in the EViews 4 econometric software package. Using the RATS 6 econometric software package yielded virtually identical results. Tables 2-7 report the CCC, VARMA-GARCH and VARMA-AGARCH estimates for the four index returns. Both the asymptotic and the Bollerslev-Wooldridge (1992) robust t-ratios are reported. In general, the robust t-ratios are smaller in absolute value than their asymptotic counterparts.

The estimates of the CCC model are given in Tables 2-3. In terms of the conditional mean, the results show insignificant autocorrelation for all four index returns. In each case, the estimated short run persistence of the index return shocks, α_i, and the contribution of the index return shocks to the long run persistence, β_i, are positive and significant.

Tables 4-5 report the estimates of the VARMA-GARCH model. Except for the DJIAs, the conditional mean estimates show insignificant autocorrelation for all four index returns. The estimates of the conditional variance show that the DJSI STOXX index returns are only affected by its own previous short run (α_{DS}) and long run (β_{DS}) shocks, while the DJSI EURO STOXX is affected by its own previous short run (α_{DES}) and long run (β_{DES}) shocks, and previous short run (α_{DS}) DJSI STOXX shocks. Therefore, volatility spillover effects are observed from DJSI STOXX to the DJSI EURO STOXX, but not the reverse.

Table 5 shows that the DJIA index returns are only affected by its own previous short run (α_D) and long run (β_D) shocks, while the S&P500 index returns are affected by previous short run (α_S and α_D) and long run (β_S and β_D) shocks in both S&P500 and DJIA. Therefore, volatility spillover effects are observed from DJIA to the S&P500, but not the reverse.

Estimates of the VARMA-AGARCH model are presented in Tables 6-7. As in the previous two tables, insignificant autocorrelation are observed for all four index returns. The estimates of the conditional variance show significant asymmetric effects of positive and negative index return shocks on the conditional volatility in all cases. In terms of the multivariate spillover effects on the conditional variance given in Table 6, the two DJSI indexes are only affected by their own previous short run and long run shocks. Similarly, the results in Table 7 show that the two financial indexes are only affected by their own previous short run and long run shocks. Unlike the case of the VARMA-GARCH model, no volatility spillover effects are observed for the four risk return indexes.

The estimated conditional volatility for the DJSI STOXX, DJSI EURO STOXX, DJIA and S&P500 for the CCC, VARMA-GARCH and VARMA-AGARCH models are plotted in Figure 3-4. Overall, there is strong evidence of volatility clustering, with the presence of some outliers and/or extreme observations. Moreover, the estimated conditional volatility for the DJSI STOXX and DJSI EURO STOXX index returns in Figure 3 for the CCC and VARMA-GARCH models are virtually identical, and differ from their VARMA-AGARCH counterpart. This is because no spillover effects were found, in general, while significant asymmetric effects of positive and negative index return shocks on the conditional volatility were observed for both DJSI indexes.

In Figure 4, the estimated conditional volatility for the CCC and VARMA-GARCH models are virtually identical only for DJIA, given the lack of spillover effects for this index. The VARMA-AGARCH estimated volatilities differ from their CCC and VARMA-GARCH counterparts for both DJIA and S&P500, due to the significant asymmetric effects between positive and negative index return shocks.

Using the estimated index return standardised shocks obtained from the CCC, VARMA-GARCH and VARMA-AGARCH models, the conditional correlation coefficients for index return shocks are calculated and reported in Table 8. It is clear that the conditional correlations for the index return shocks between the two DJSI indexes and financial indexes, respectively, are very high and virtually identical for all three models. This implies that the two DJSI indexes, namely DJSI STOXX and DJSI EURO STOXX, are close substitutes in terms of the shocks to their index returns. The same holds for the two financial indexes, namely DJIA and S&P500.

6. CONCLUSION

Environmental issues have become increasingly important in economic research and policy for sustainable development. For this reason, a critical assessment of the Dow Jones Sustainable Indexes (DJSI) is crucial in order to track such issues. The purpose of this paper was to analyse the trends and volatility in DJSI indexes using daily data for the period 31 December 1998 to 1 March 2004. Moreover, the trends and volatility of two prominent financial indexes, namely DJIA and S&P500, were analysed in the same manner to provide a comparison of the time series performance of the two types of indexes.

Conditional variances of index returns were modelled using three multivariate constant conditional correlation generalised autoregressive conditional heteroscedasticity (GARCH) models, namely CCC, VARMA-GARCH and VARMA-AGARCH. The VARMA-GARCH model captured spillover effects in the volatility of the DJSI EURO STOXX from DJSI STOXX and S&P500 from DJIA. While no spillover effects were captured by the VARMA-AGARCH model, significant asymmetric effects of positive and negative index return shocks on the conditional volatility were found for all four indexes.

Overall, there was strong evidence of volatility clustering, with the presence of some outliers and/or extreme observations for the four index series. The conditional correlations for the index return shocks between the two DJSI indexes and financial indexes, respectively, were very high and virtually identical for all three models. This implies that the two DJSI indexes, namely DJSI STOXX and DJSI EURO STOXX, are close substitutes in terms of the shocks to their index returns. The same holds for the two financial indexes, namely DJIA and S&P500.

AKNOWLEDGEMENTS

The authors would like to thank Kathrin Füllemann of SAM Indexes GmbH for helpful information. The first two authors wish to acknowledge the financial support of the Australian Research Council.

REFERENCES

Berndt, E.K., B.H. Hall, R.E. Hall and J.A. Hausman (1974), Estimation and inference in nonlinear structural models, *Annals of Economic and Social Measurement*, 3, 653-665.

Bollerslev, T. (1986), Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31, 307-327.

Bollerslev, T. (1990) Modelling the coherence in short-run nominal exchange rate: A multivariate generalized ARCH approach, *Review of Economics and Statistics*, 72, 498-505.

Bollerslev, T. and J.M. Wooldridge (1992), Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, *Econometric Reviews*, 11, 143-173.

Hoti, S., F. Chan and M. McAleer (2002), Structure and asymptotic theory for multivariate asymmetric volatility: Empirical evidence for country risk ratings, paper presented to the Australasian Meeting of the Econometric Society, Brisbane, Australia, July 2002.

Hoti, S., M. McAleer and L.L. Pauwels (2005a), Modelling Environmental Risk, to appear in *Environmental Modelling and Software.*

Hoti, S., M. McAleer and L.L. Pauwels (2005b), Measuring Environmental Risk, to appear in *Journal of Economic Surveys.*

Engle, R.F. (1982), Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica*, 50, 987-1007.

Glosten, L., R. Jagannathan and D. Runkle (1992), On the Relation Between the Expected Value and Volatility of Nominal Excess Returns on Stocks, *Journal of Finance*, 46, 1779-1801.

Li, W.K., S. Ling and M. McAleer (2002), Recent Theoretical Results for Time Series Models with GARCH Errors, *Journal of Economic Surveys*, 16, 245-269. Reprinted in M. McAleer and L. Oxley (eds.), *Contributions to Financial Econometrics: Theoretical and Practical Issues*, Blackwell, Oxford, 2002, pp. 9-33.

Ling, S. and M. McAleer (2002a), Necessary and Sufficient Moment Conditions for the GARCH(r,s) and Asymmetric Power GARCH(r,s) Models, *Econometric Theory*, 18, 722-729.

Ling, S. and M. McAleer (2002b), Stationarity and the Existence of Moments of a Family of GARCH Processes, *Journal of Econometrics*, 106, 109-117.

Ling, S. and M. McAleer (2003), Asymptotic Theory for a Vector ARMA-GARCH Model, *Econometric Theory*, 19, 278-308.

McAleer, M. (2005), Automated inference and learning in modeling financial volatility, *Econometric Theory*, 21, 232-261.

Nelson, D.B. (1991), Conditional heteroscedasticity in asset returns: A new approach, *Econometrica*, 59, 347-370.

Wong, H. and W.K. Li (1997), On a multivariate conditional heteroscedasticity model, *Biometrika*, 4, 111-123.

AUTHORS' BIOGRAPHIES

SUHEJLA HOTI is an ARC Research Fellow in the School of Economics and Commerce, University of Western Australia. Her research interests are in macroeconomics, country risk, environmental risk, environmental modelling, finance, financial econometrics, time series analysis, and tourism research.

MICHAEL MCALEER is Professor of Economics (Econometrics) in the School of Economics and Commerce, University of Western Australia. His research interests are in econometrics, financial econometrics, finance, statistics, time series analysis, intellectual property, integrated environmental systems, environmental risk, and tourism research.

LAURENT L. PAUWELS is a PhD student in the Economics Section, Graduate Institute of International Studies, Geneva. His research interests are in macroeconomics, financial econometrics, environmental risk, and environmental modelling.

Table 1: Unit Root Test Statistics for Daily Stock Indexes

Indexes (Logarithms)	ADF	Phillips-Perron
DJSI STOXX	-1.244	-1.323
DJSI EURO STOXX	-1.433	-1.518
DJIA	-2.587	-2.741
S&P500	-1.758	-1.893

Note: The simulated critical value at 5% level of significance is -3.4156.

Indexes (Log-differences)	ADF	Phillips-Perron
DJSI STOXX	-18.077	-36.264
DJSI EURO STOXX	-17.512	-36.033
DJIA	-17.516	-37.821
S&P500	-18.166	-37.986

Note: The simulated critical value at 1% level of significance is -2.5673.

Table 2: CCC Estimates for Environmental Sustainability Indexes

Data	Conditional Mean		Conditional Variance		
	θ_1	θ_2	ω	α	β
DJSI STOXX	2.9E-04 0.942 0.938	0.006 0.187 0.196	4.7E-06 3.132 2.966	0.096 6.433 4.422	0.875 43.709 35.442
DJSI EURO STOXX	3.0E-04 0.818 0.841	0.012 0.415 0.425	4.9E-06 2.917 3.005	0.085 6.879 4.350	0.896 56.739 57.973

Note: The three entries corresponding to each parameter are their estimates, their asymptotic t-ratios, and the Bollerslev and Wooldridge (1992) robust t-ratios.

Table 3: CCC Estimates for Financial Indexes

Data	Conditional Mean		Conditional Variance		
	θ_1	θ_2	ω	α	β
DJIA	4.8E-04 1.599 1.704	-0.033 -1.144 -1.139	2.4E-06 2.840 2.443	0.070 6.187 4.351	0.916 70.887 50.312
S&P500	2.7E-04 0.858 0.887	-0.032 -1.072 -1.191	2.5E-06 2.539 2.489	0.064 5.584 4.333	0.922 62.185 56.354

Note: The three entries corresponding to each parameter are their estimates, their asymptotic t-ratios, and the Bollerslev and Wooldridge (1992) robust t-ratios.

Table 4: VARMA-GARCH Estimates for Environmental Sustainability Indexes

Data	Conditional Mean		Conditional Variance				
			Own Effects			Spillover Effects	
DJSI	θ_1	θ_2	ω_{DS}	α_{DS}	β_{DS}	α_{DES}	β_{DES}
STOXX	2.2E-04 0.707 0.708	0.011 0.355 0.374	5.3E-06 2.162 1.953	0.106 2.435 2.132	0.794 7.865 8.537	-0.002 -0.073 -0.067	0.047 0.824 0.923

Data	Conditional Mean		Conditional Variance				
			Own Effects			Spillover Effects	
DJSI EURO	θ_1	θ_2	ω_{DES}	α_{DES}	β_{DES}	α_{DS}	β_{DS}
STOXX	4.9E-05 0.130 0.133	0.021 0.718 0.752	4.2E-06 3.741 2.813	0.031 1.617 1.451	0.937 56.739 33.175	0.068 2.337 1.932	-0.048 -1.840 -1.024

Notes: The three entries corresponding to each parameter are their estimates, their asymptotic t-ratios, and the Bollerslev and Wooldridge (1992) robust t-ratios. DS and DES refer to DJSI STOXX and DJSI EURO STOXX, respectively.

Table 5: VARMA-GARCH Estimates for Financial Indexes

Data	Conditional Mean		Conditional Variance				
			Own Effects			Spillover Effects	
DJIA	θ_1	θ_2	ω_D	α_D	β_D	α_S	β_S
	5.9E-04 2.007 2.115	-0.035 -1.242 -1.213	2.4E-06 2.591 2.178	0.088 3.982 2.538	0.912 37.285 26.560	-0.019 -1.038 -0.588	0.005 0.225 0.156

Data	Conditional Mean		Conditional Variance				
			Own Effects			Spillover Effects	
S&P500	θ_1	θ_2	ω_S	α_S	β_S	α_D	β_D
	-3.3E-04 -1.118 -1.236	-0.011 -0.400 -0.805	1.7E-05 0.864 32.640	-0.075 -5.680 -4.249	-0.921 -54.639 -27.132	0.148 8.184 7.001	1.926 11.498 19.143

Notes: The three entries corresponding to each parameter are their estimates, their asymptotic t-ratios, and the Bollerslev and Wooldridge (1992) robust t-ratios. D and S refer to DJIA and S&P500, respectively.

Table 6: VARMA-AGARCH Estimates for Environmental Sustainability Indexes

Data	Conditional Mean		Conditional Variance					
			Own Effects				Spillover Effects	
DJSI	θ_1	θ_2	ω_{DS}	α_{DS}	γ_{DS}	β_{DS}	α_{DES}	β_{DES}
STOXX	-2.0E-04	0.017	4.5E-06	-0.022	0.174	0.860	0.002	0.029
	-0.648	0.585	3.258	-0.719	5.112	27.454	0.082	1.447
	-0.658	0.653	2.629	-0.818	4.651	17.173	0.098	1.082

Data	Conditional Mean		Conditional Variance					
			Own Effects				Spillover Effects	
DJSI	θ_1	θ_2	ω_{DES}	α_{DES}	γ_{DES}	β_{DES}	α_{DS}	β_{DS}
EURO	-1.9E-04	0.031	4.2E-06	-3.5E-04	0.125	0.900	-0.002	0.032
STOXX	-0.503	1.034	2.466	-0.017	4.356	40.447	-0.063	0.750
	-0.511	1.178	2.178	-0.013	3.965	20.921	-0.052	0.477

Notes: The three entries corresponding to each parameter are their estimates, their asymptotic t-ratios, and the Bollerslev and Wooldridge (1992) robust t-ratios. DS and DES refer to DJSI STOXX and DJSI EURO STOXX, respectively.

Table 7: VARMA-AGARCH Estimates for Financial Indexes

Data	Conditional Mean		Conditional Variance					
			Own Effects				Spillover Effects	
DJIA	θ_1	θ_2	ω_D	α_F	γ_D	β_D	α_S	β_S
	3.6E-05	-0.040	1.5E-06	-0.006	0.142	0.917	-0.014	0.023
	0.125	-1.443	1.792	-0.490	6.509	48.494	-0.952	1.404
	0.132	-1.420	1.777	-0.422	6.395	48.112	-0.980	1.391

Data	Conditional Mean		Conditional Variance					
			Own Effects				Spillover Effects	
S&P500	θ_1	θ_2	ω_S	α_S	γ_S	β_S	α_D	β_D
	-3.9E-04	-0.024	2.3E-06	-0.083	0.185	0.918	0.045	0.026
	-1.303	-0.828	2.695	-6.458	7.416	45.322	3.375	1.431
	-1.208	-1.058	2.507	-3.692	5.420	37.527	1.632	0.929

Note: The three entries corresponding to each parameter are their estimates, their asymptotic t-ratios, and the Bollerslev and Wooldridge (1992) robust t-ratios. D and S refer to DJIA and S&P500, respectively.

Table 8: CCC Conditional Correlations

Index Pairs	CCC	VARMA-GARCH	VARMA-AGARCH
(DJSI STOXX, DJSI EURO STOXX)	0.946	0.946	0.946
(DJIA, S&P500)	0.927	0.923	0.920

Figure 1: Daily Data for Sustainability Indexes (left) and Index Returns (right)

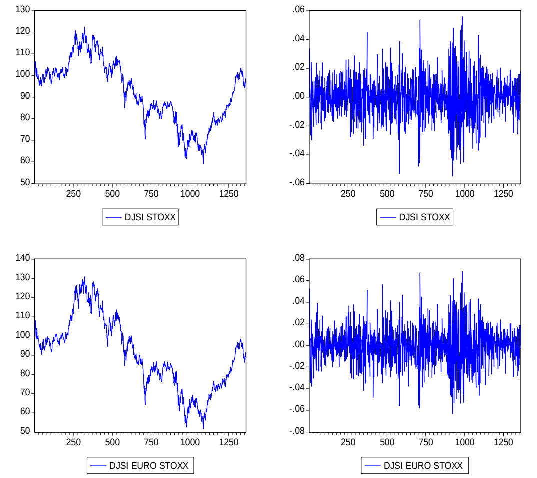

Figure 2: Daily Data for Financial Indexes (left) and Index Returns (right)

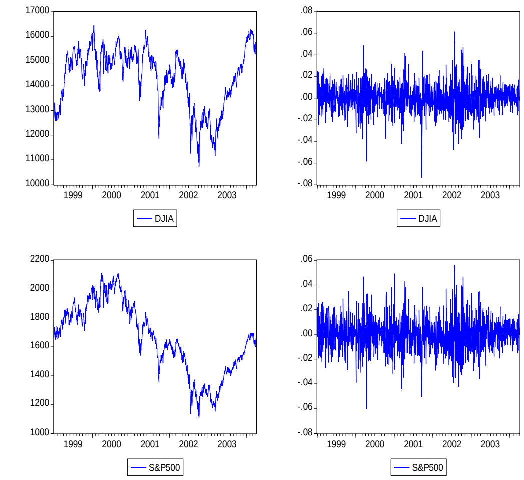

Figure 3: Sample and Estimated Volatility

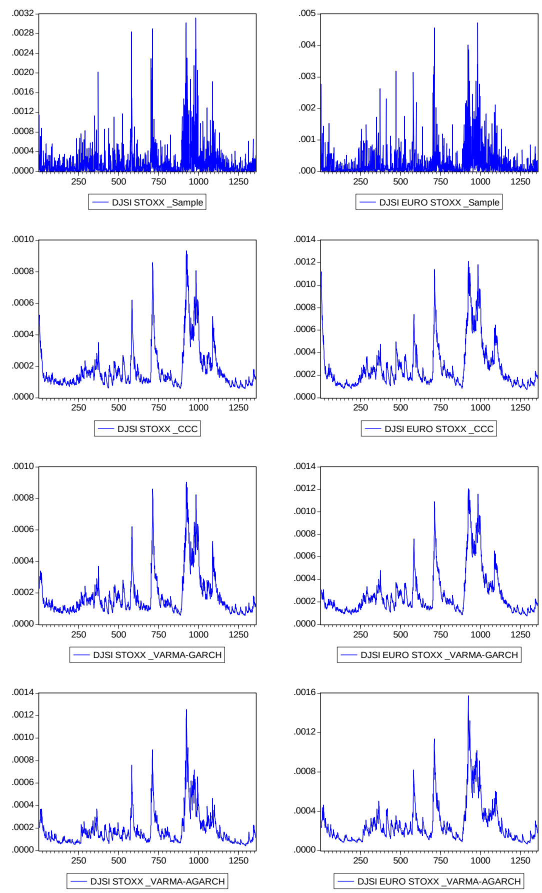

Figure 4: Sample and Estimated Volatility