THE PREDICTABILITY OF THE SOCIALLY RESPONSIBLE INVESTMENT INDEX: A NEW TMDCC APPROACH

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ABSTRACT. This study extends the threshold error-correction model of Enders and Siklos (2001) to the momentum threshold error-correction model with the dynamic conditional correlation GARCH model of Engle (2002), in order to investigate the asymmetric cointegration and causal relationships between the FTSE4GOOD index and the U.S. stock index. The results reveal that the responsible investment index and stock indexes adjust asymmetrically back to the long-run equilibrium relationship. Consequently, the stock index has a dominant impact on the responsible investment index and such a finding could prove valuable to investors when forecasting the responsible investment index.

1. INTRODUCTION

In recent years, the area of socially responsible investment has become an interesting topic for research. According to modern portfolio theory, an increasing number of investors will seek to reduce risk through diversification and to maximize their long-term returns through socially responsible investment. Moreover, the socially responsible investment gives the institutional and individual investors the opportunity to meet their needs and objectives. Therefore, the socially responsible investment is an interesting topic for our research.

As highlighted earlier, only a few studies have examined the responsible investment index issue. Hussein (2004) analyzed the performance of the FTSE-GII, FTSE4Good Global and FTSE All-World indices and indicated that the FTSE4Good index outperformed the FTSE All-World index during the overall and bull market periods as measured by the risk-adjusted returns, the Sharpe, Jansen and Treynor ratios and by long-run performance in general. Hoti et al. (2007) used GARCH models and found that five sustainability and ethical indices exhibited co-national volatility clustering and asymmetric volatility effects. Hoti et al. (2008) found that the Dow Jones Sustainability Index (hereafter DJSI) and the Ethibel Sustainability Index gave rise to spillover effects, while the only spillover effect from the Dow Jones Industrial Average Index (hereafter DJAI) to the DJSI returns was found to be that based on the vector ARMA-GARCH model. Nikolaos et al. (2009) found macroeconomic factors to have an impact on the responsible investment index using the GARCH model.

A great number of researches have tested the lead-lag relationship between the two market prices; motivated by the investors who can earn abnormal profits from one market information to trade another market. To our knowledge, few studies have sought to investigate the lead-lag relationship between the responsible investment index and stock market index. The corporations with good corporate socially responsible (hereafter CSR) practices can lead to correct information for investors; then, from this information may be understood the price change in

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the future. Therefore, the responsible investment index, which is composed of the companies with high corporate social responsibility, may lead to the stock market index. However, the corporations with good CSR practices have higher costs than other companies with no good CSR practices. The corporations with good CSR practices will increase money in social responsibility practices when they have high profit; moreover, the price of the corporations does not easy to large change. Thus, the stock market index leads to the responsible investment index. This study attributes importance to examination of the causal relationships between the responsible investment index returns and stock market index returns.

Understanding the long-run relationship by cointegration techniques between stock prices is highly important in portfolio theory. The investors understand that these stock prices have a common stochastic trend and a long-run relationship; thus, investors will reduce benefits from long run diversification. Most previous studies that examined the traditional time series model assumed that the underlying variables exhibited symmetrical adjustment processes. However, Balke and Fomby (1997), Enders and Granger (1998), and Enders and Siklos (2001) have demonstrated the problem of the low power of traditional cointegration tests. Thus, Enders and Siklos (2001) introduced the threshold autoregressive (TAR) and momentum threshold autoregressive (MTAR) models as solutions to the low power of traditional cointegration tests. Up to now, few studies investigate the asymmetric long-run relationship between the responsible investment index and the stock market index, in order to provide investors with an understanding of whether the two markets have benefits from long run diversification.

Hoti et al. (2007), Hoti et al. (2008) and Nikolaos et al. (2009) used responsible investment index data to demonstrate high volatility clustering and Hoti et al. (2008) used a multivariate GARCH model to investigate the responsible investment index and the stock index. Our study extends the MTAR model by Enders and Siklos (2001) to an MTAR with multivariate GARCH (hereafter TMGARCH) model. Unfortunately, the constant correlation specification of multivariate GARCH has a generally well-behaved likelihood function, but all these models are mis-specified by the statistical tests. However, the dynamic conditional correlation (DCC) model allows these correlations to be time-varying. The dynamic conditional correlation and the bivariate GARCH model adequately describe the time-varying conditional correlation phenomenon of returns on financial assets as discussed by Engle (2002) and Tse and Tsui (2002). The major advantage is the simultaneous investigation of nonlinearity cointegration and timevarying correlations. The field of research contributes significantly to the MTAR and DCC model; thus, this study intends to incorporate DCC into the TMGARCH (hereafter TMDCC) to analyze the dynamic relationship between the responsible investment index and stock index.

This research, by using a new TMDCC approach, aims to investigate the asymmetric cointegration and causal relationships between the responsible investment index and the stock index in the US. Our study, which fills a gap in the literature on the responsible investment index issue, finds an asymmetrical long-run relationship; therefore, investors will reduce benefits from long run diversification. The empirical result finds that the stock index has a unidirectional relationship between stock indices (DJAI and SP returns) and the responsible investment index (FTSE_US index returns). Moreover, this study reports the negative relationship between DJAI and SP returns and FTSE_US index returns. There results provide valuable investment implications.

The remainder of this paper is organized as follows. Section 2 describes the data and introduces the methodology. Section 3 then analyzes the empirical findings. Finally, the conclusions are presented in Section 4.

2. DATA AND METHODOLOGY

The sample period runs from January 1, 2006 to September 30, 2010. Daily data based on the DJAI, S&P 500 (hereafter SP) and FTSE4Good US index (hereafter FTSE_US). This paper were collected and transformed into daily returns, yielding 1,195 observations. The daily financial data were obtained from the Datastream database. Using the methodology of the threshold cointegration test of Enders and Granger (1998), the completion of the TAR model required two steps. By assuming that the variables x_t and y_t follow an I(1) process, the first regression takes the form

$$y_t = \alpha + \beta x_t + \varepsilon_t, \tag{2.1}$$

where ε_t is the stochastic disturbance term. A regression of the form

$$\Delta \varepsilon_t = I_t \rho_1 \varepsilon_{t-1} + (1 - I) \rho_2 \varepsilon_{t-1} + \sum_{i=1}^l \gamma_i \Delta \varepsilon_{t-i} + \mu_t, \qquad (2.2)$$

is then taken, where $\{\varepsilon_t\}$ contains the regression residuals from Eqn.(2.1), μ_t is an i.i.d. disturbance with zero mean, and I_t is the Heaviside indicator such that,

$$I_t = \begin{cases} 1 & if \quad \varepsilon_{t-1} \ge 0 \\ 0 & if \quad \varepsilon_{t-1} < 0 \end{cases} \quad or \quad I_t = \begin{cases} 1 & if \quad \varepsilon_{t-1} \ge \tau \\ 0 & if \quad \varepsilon_{t-1} < \tau \end{cases}$$
(2.3)

where τ is the threshold value. This study adopts the method of Chan (1993) to obtain a consistent estimate of the threshold used by Enders and Siklos (2001). When $\varepsilon_{t-1} > \tau$, Eqn.(2.3) becomes $\Delta \varepsilon_t = I_t \rho_1 \varepsilon_{t-1} + \sum_{i=1}^l \gamma_i \Delta \varepsilon_{t-i} + \mu_t$, otherwise $\Delta \varepsilon_t = \rho_2 \varepsilon_{t-1} + \sum_{i=1}^l \gamma_i \Delta \varepsilon_{t-i} + \mu_t$ is used. Enders and Granger (1998) and Caner and Hansen (1998) claim that it is also possible to allow the Heaviside indicator to depend on the change in ε_{t-1} (namely, $\Delta \varepsilon_{t-i}$) rather than the level of ε_{t-1} ; the Momentum Threshold Autoregressive (MTAR) model. The Heaviside indicator of Eqn. (2.3) then becomes,

$$\mathbf{I}_{t} = \begin{cases} 1 & \text{if } \Delta \varepsilon_{t-1} \ge 0\\ 0 & \text{if } \Delta \varepsilon_{t-1} < 0 \end{cases} \quad \text{or} \quad \mathbf{I}_{t} = \begin{cases} 1 & \text{if } \Delta \varepsilon_{t-1} \ge \tau\\ 0 & \text{if } \Delta \varepsilon_{t-1} < \tau \end{cases}$$
(2.4)

The MTAR model implies that the adjustment mechanism of ε_t is dynamic, since the spread is widening (narrowing) when $\Delta \varepsilon_{t-1}$ is greater (less) than the threshold value.¹

This study extends the MTAR model to the TMDCC model to investigate the asymmetric cointegration and causal relationships between the FTSE_US index and DJAI or SP. The TMDCC model is expressed as

$$Y_{k,t} = \mu_{0,k} + \gamma_{1,k} Z_{t-1}^{+} + \gamma_{2,k} Z_{t-1}^{-} + \sum_{i=1}^{m} \theta_{i,k} R_{t-i} + \sum_{j=1}^{n} \pi_{j,k} F_{t-j} + \sqrt{h_{k,t}} \varepsilon_{k,t}$$
(2.5)

where $Y_{k,t}$ represents the returns of k asset and k = (R, F) represents the stock indices and FTSE_US. $Z_{t-1}^+ = I_t \hat{u}_{t-1}$ and $Z_{t-1}^- = (1 - I_t) \hat{u}_{t-1}$ such that $I_t = 1$ if $u_{t-1} \ge \tau$, $I_t = 0$ if $u_{t-1} \le \tau$. The Granger-Causality tests are performed by testing whether all the coefficients of $\pi_{j,R}$ or $\theta_{i,F}$ differ statistically from zero according to the significance of a standard F-test.

The disturbance error terms of the mean equations (ε_t) are assumed to be conditional multivariate normal with mean zero and conditional covariance matrix H_t. The disturbance error term and conditional covariance matrix can be expressed as

$$\varepsilon_{t} = \begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{F,t} \end{bmatrix} \left| \Omega_{t-1} \sim N(0, H_{t}) \text{ and } H_{t} = \begin{bmatrix} h_{R,t} & h_{RF,t} \\ h_{FR,t} & h_{F,t} \end{bmatrix} \right|$$
(2.6)

where ε_t is a vector of errors given the past information Ω_{t-1} . The conditional variancecovariance matrix can be written as $H_t = D_t V_t D_t$ where $D_t = \text{diag} \{\sqrt{h_{i,t}}\}$ and V_t is a 2×2 diagonal matrix of conditional standard deviations. The h_t^i is the estimated conditional variance from the individual standard univariate GARCH(1,1) models that are expressed as:

¹For any value of τ , some papers have demonstrated that the sufficient and necessary conditions for ε_t to be stationary are $\rho_1 < 0$, $\rho_2 < 0$, and $(1+\rho_1)(1+\rho_2) < 1$. This representation not only captures the asymmetric effect, but can also test the long-run relationship between x_t and y_t .

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$$\mathbf{h}_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \mathbf{h}_{i,t-1} \text{ where } \mathbf{i} = \mathbf{R} \text{ or } \mathbf{F}$$

$$(2.7)$$

where each market's conditional variance $(h_{i,t})$ is modeled as a function of the constant term, the square of the last period's own residuals $\varepsilon_{i,t-1}^2$, and its lagged conditional variance $h_{i,t-1}$. Engle also suggests estimating the following time-varying correlation process

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{ij,t}}}$$
(2.8)

$$q_{ij,t} = (1 - A - B) \overline{q} + A q_{ij,t-1} + B \eta_{i,t-1} \eta_{i,t-1} \text{ where } i, j = R, F \text{ and } i \neq j$$

$$(2.9)$$

where \overline{q} represents the unconditional expectation of the cross product $\eta_{i,t}\eta_{j,t}$. $\eta_{i,t}$ and $\eta_{j,t}$ are the standardized residuals with zero mean and a variance of one. The $Aq_{ij,t-1}+B\eta_{i,t-1}\eta_{j,t-1}$ show the conditional time-varying covariance.

3. EMPIRICAL ANALYSIS

The descriptive statistics for the DJAI, SP and FTSE US returns are reported in Table 1. It is found that the average returns of the DJAI, SP and FTSE US were -0.0005, -0.0089 and -0.0112, respectively. The standard deviation of DJAI is lower than that of SP and FTSE US. The Jarque-Bera statistics indicate that the distribution of these three commodities' returns in both time periods has a sharper peak than the normal distribution. The statistics also show that most of the returns in the periods are negatively skewed except for DJAI, and the leptokurtosis implies that the distribution of returns has a fatter tail than the normal distribution. However, the statistics show that the skewness is insignificant at the 10% level except in the case of SP. The Q and Q2 tests of three series are both significant and diagnose clustering, correlation, and heteroskedasticity, which indicates that the GARCH model is appropriate for the analysis of the data. This study uses the Augmented Dickey-Fuller test to check for stationarity in the returns of DJAI, SP and FTSE US. These tests are designed to indicate whether all the series are non-stationary in terms of their levels and stationary in terms of their first differences. This study thus suggests that they are integrated of order one, I(1).

Table 1. Descriptive statistics of returns							
Items	DJAI	SP	FTSE_US				
Mean	-0.0005	-0.0089	-0.0112				
SD	1.4636	1.6056	1.6266				
Skewness	0.0318	-0.2177^{***}	-0.0757				
Kurtosis	11.5421^{***}	11.2267***	10.8128^{***}				
Jarque-Bera	3630.3250^{***}	3376.4240^{***}	3037.8350^{***}				
Q(4)	43.0428***	41.5888^{***}	32.2472^{***}				
$Q^{2}(4)$	372.6474^{***}	371.6632^{***}	313.3702***				

Notes: SD denotes standard error. Q(4) and $Q^2(4)$ denote the Ljung-Box Q and Q2 statistics with 4 lags. The Jarque-Bera test represents the normality test. *** denotes rejection of the hypothesis at the 1% level.

In the table 2, this study also finds these models with the threshold value τ to be better than in the case where a threshold value of 0 is assumed based on the AIC and SBC criterion and the best threshold values obtained are 0.0148 and 0.0065 for the MTAR model for the DJAI-FTSE US and SP-FTSE US data, respectively, using the method of Chan (1993).²

In terms of the MTAR model with the best threshold values, this paper found three results as shown in Table 2 and present two spread graphs in Figure 1 and 2. First, the two \hat{F}_{C} -statistics based on the MTAR model with the best threshold values exceed the respective critical values, indicating that the null hypothesis of no cointegration is also rejected. Second, the two F_A -statistics exceed the respective critical value, indicating that the null hypothesis

²This study finds the MTAR model to be better than the TAR model.

of the symmetric adjustment process is also rejected. Finally, the study found that $|\rho_1| > |\rho_2|$, indicating that increases in the spread tend to revert back toward the threshold faster than corresponding decreases. Consequently, this study shows that the relationship between the social responsibility index and stock index adjusts asymmetrically back to the long-run equilibrium and that the speed of adjustment when the spread is widening is faster than that when the spread is becoming narrower. This study finds a common stochastic trend as regards asymmetric adjustment process between the responsible investment index and the stock market index. As a consequence, the investors will reduce benefits from long run diversification between the responsible investment index and the stock market index.

\mathbf{FTSE} _US							
Items	DJAI- FTSE_US		SP- FTSE_US				
Threshold Value	0	0.0148	0	0.0065			
$ ho_1$	-0.0049	-0.7774	-0.008	-0.119			
$ ho_2$	-0.0065	-0.0055	-0.0093	-0.0053			
AIC	-4835.64	-4860.37	-5592.75	-5617.93			
SBC	-4820.39	-4845.12	-5577.49	-5602.68			
\widehat{F}_{A}	2.3153^{*}	14.8275^{***}	2.6614^{*}	15.4118^{***}			
\widehat{F}_{C}	0.0842	25.0134^{***}	0.026	25.4125^{***}			

Table 2. Momentum threshold cointegration test between DJAI, SP and ETSE US

Notes: \widehat{F}_A and \widehat{F}_C denote the null hypothesis of no cointegration and symmetry, respectively. *, ** and *** denotes significance at the 10%, 5% and 1% levels, respectively.

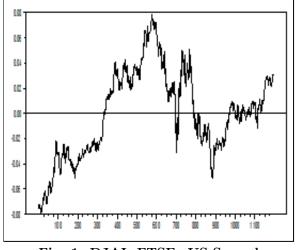
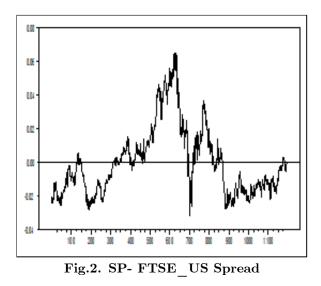


Fig. 1. DJAI- FTSE US Spread

Table 3 shows the estimates of TMDCC between the stock indexes and FTSE_US. The Q and Q2 tests of the standard residuals are all insignificant and no clustering, no correlation, and no heteroskedasticity are found, implying that the TMDCC model has sufficient explanatory power in regard to the data. The value of $\alpha_i + \beta_i$ is smaller than one and close to one for all series, which indicates that these results conform to the process, and remains stationary in the GARCH model. Therefore, this study reports that the responsible investment index returns have high volatility clustering; a finding which is consistent with Hoti et al. (2007), Hoti et al. (2008) and Nikolaos et al. (2009). In table 3, the coefficient estimated values of A and B are significant at the 1% significance level, implying that the explanatory ability of the bivariate GARCH(1,1) model with a DCC is better than that of the bivariate GARCH model with a constant conditional correlation.



This result is consistent with the findings of Engle (2002). As a consequence, these findings are high volatility clustering and dynamic correlation between the responsible investment index returns and the stock market index returns.

$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	<u>Table 3.</u>	<u>The estim</u>	ated results	of the TM	<u>DCC Mode</u> l	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Items			$^{\mathrm{SP}}$	FTSE_US	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\mu_{0,k}$	0.0379^{***}	0.0229**	0.0290	0.0274	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\gamma_{1,\mathbf{k}}$	95.2214^{***}	127.5191^{***}	-15.9902	-17.5855	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\gamma_{2,\mathbf{k}}$	-1.5539^{***}	-1.4322^{***}	-3.4065^{**}	-2.7366*	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		-0.0672***	-0.0374**	-0.2760**	-0.2633**	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\pi_{1,\mathbf{k}}$	-0.0138		0.1882	0.1758	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	ω_i			0.0167^{***}	0.0162^{***}	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	α_i		0.0753^{***}	0.0826^{***}		
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	β_i	0.9131^{***}	0.9193^{***}	0.9128^{***}	0.9166^{***}	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	А	0.0467***		0.0521^{***}		
$\begin{array}{ccccccc} F2 & 5.8656^{**} & 4.3210^{**} \\ Q(4) & 3.508 & 1.145 & 4.155 & 3.969 \\ Q^2(4) & 5.803 & 5.576 & 5.628 & 6.138 \end{array}$	В	0.9474^{***}		0.9424^{***}		
$\begin{array}{ccccccc} Q(4) & 3.508 & 1.145 & 4.155 & 3.969 \\ Q^2(4) & 5.803 & 5.576 & 5.628 & 6.138 \end{array}$	F1	0.8730		2.4711		
$Q^{2}(4)$ 5.803 5.576 5.628 6.138	F2		5.8656^{**}		4.3210**	
	Q(4)	3.508	1.145	4.155	3.969	
LL -2068.5083 -1802.7098	$Q^{2}(4)$	5.803	5.576	5.628	6.138	
	LL	-2068	8.5083	-1802.7098		

Notes: *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. The Q(4) and $Q^2(4)$ are Ljung-Box Q^2 statistics with 4 lags. LL is the Log Likelihood. F1 is $H_0: \theta_{1,k} = 0$, F2 is $H_0: \pi_{1,k} = 0$.

This study finds that the relationship between the social responsibility index and the stock indices adjusts more slowly to a narrowing of the spread ($|\gamma_1|=95.2214$ or 127.5191 in model 1 and $|\gamma_1|=15.9902$ or 17.5855 in model 2) than to a widening of the spread ($|\gamma_2|=1.5539$ or 1.4322 in model 1 and $|\gamma_2|=3.4065$ or 2.7366 in model 2), indicating that increases in the spread between the responsible investment index and the stock market index tend to revert back towards the threshold faster than the corresponding decreases, a finding that is consistent with the MTAR models.

In table 3, the estimated results of $F1(H_0: \pi_{1,F} = 0)$ are not significant at the 10% significance level and of F2 ($H_0: \theta_{1,R} = 0$) are significant at the 5% significance level. As for the causal relationship between the social responsibility index and the stock indices, this research finds evidence of a unidirectional relationship between DJAI and SP and FTSE_US. The estimated results ($\theta_{1,R} = -0.0374$ and -0.2633) are significantly negative at the 5% level. This study finds evidence of the negative relationship between DJAI and SP returns and FTSE_US index returns. The investor will invest stock with good CSR practices to avoid loss when the market returns decrease. Thus, this result in a decrease in the stock index accompanying an increase in the social responsibility index, implying the investor can purchase the social responsibility ETFs or stocks.

In other words, a unidirectional relationship exists from the S&P500 and Dow Jones Average index to the FTSE_US, implying that such a finding could prove valuable to individual investors and financial institutions since the S&P500 and Dow Jones Average index could be used to forecast the FTSE_US. Therefore, there are two investment implications in that arbitrage can take place when there is disequilibrium between the stock indices and the social responsibility index can be understood by using the stock indices when investors are engaged in related socially-responsible investments.

4. CONCLUSION

This paper uses the threshold cointegration test to investigate the asymmetric long-run relationship and applies the TMDCC model to examine the causal relationship between the responsible investment index and stock market indices.

The empirical result shows that the responsible investment index returns are high volatility clustering. Furthermore, there is dynamic correlation between the responsible investment index returns and the stock market index returns. There is an asymmetric long-run relationship with the asymmetric adjustment process between the responsible investment index and the stock market indices. In addition, the speed of adjustment when the spread is widening is faster than when the spread is narrowing. The long-run relationship between the responsible investment index and the stock market indices indicates investors will reduce benefits from long run diversification. However, this paper finds evidence of a unidirectional relationship between DJAI and SP and FTSE US.

There are two major financial points. This finding has been provided that investors engaged in construction of long-run investment portfolios between the responsible investment index and stock market indices. Moreover, this lead-lag information offer new evidence in support of the existence of SP and DJSI stock index forecast power the socially-responsible investments, indicating the investors use the information from SP and DJSI stock index to purchase the social responsibility ETFs or stocks.

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