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ESTIMATING TIME-VARYING CONDITIONAL CORRELATIONS BETWEEN ECONOMIC GROWTH AND CARBON DIOXIDE EMISSIONS VOLUME

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Abstract. There has been extensive research on the historical relationship between economic growth and carbon dioxide emissions. Presently, it can be assumed that the high carbon dioxide emissions volume in the world is the result of economic growth. However, over the last couple of decades, increasing awareness about environmental problems, which has resulted from the new realities of the world such as climate change, emphasises the importance of a low-carbon economy. Under these new circumstances that the world faces, many countries, especially in the developed world, have already started to work for the transition to a low-carbon economy. Hence, in some countries, carbon dioxide (CO_2) emissions have started to decelerate despite accelerating economic growth. In this paper, the dynamic conditional correlations (DCC) model is used to estimate time-varying conditional correlations between economic growth and carbon dioxide emissions in the United States of America (USA) between 1800 and 2006. The empirical results indicate that two variables are positively and highly correlated until the 1970's. The results also indicate that volatility in correlation over the period 1800–1970 is low. The results further indicate that the correlation between economic growth and carbon dioxide emissions volume is highly volatile during the period 1970–2006. There seems to be a downward trend in correlation between two variables in this period.

Keywords: carbon dioxide emissions, economic growth, multivariate GARCH, conditional correlation, low-carbon economy.

AIMS AND BACKGROUND

During the last century, many environmental problems have entered the world stage. However, climate change has become, certainly, the most important one with far-reaching consequences for the mankind. Climate change is the outcome of increasing emissions of greenhouse gases (mainly carbon dioxide) in the atmosphere which leads to the warming of the earth[1]. If not controlled, this increase is expected to have devastating consequences like severe droughts and flooding in areas which are presently farming regions, shortage of drinking water, increasing number of natural events like storms and hurricanes, damaged ecological systems, sea-level rises, redistribution of natural resources and immigration[2].

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Behind this threatening scenario lies the historical linkage between economic growth and carbon dioxide emissions. Recently, low-carbon development paths have started to be encouraged by many countries as well as the international community for a sustainable future[3]. In a low-carbon economy, economic growth can continue sustainably while emissions show a decline[4]. In parallel, this study proposes that continuing economic growth measured by the increase in gross domestic product (GDP) will be followed by a deceleration of carbon dioxide emissions in the years to come. In this respect, the aim of this paper is to examine the relationship between economic growth and carbon dioxide emissions in the USA for the period 1800–2006. To investigate the relationship between two variables, we estimate a recently proposed representative of the class of multivariate generalised autoregressive conditional heteroscedasticity (GARCH) models, the so-called dynamic conditional correlation (DCC) model[5]. This model calculates the current correlation between variables as a function of past realisations of volatility within the variables as well as the correlations between the variables.

EXPERIMENTAL

In this paper, the DCC model of Engle[5] was used to investigate time-varying correlations between real GDP growth and carbon dioxide emissions volume over the period 1800–2006. In contrast to the traditional time invariant correlation measure, the DCC models the second moments of series and calculates time variant correlations to analyse time varying nature of correlation patterns.

The DCC model assumes that the logarithmic changes of k variables, r_t, are conditionally multivariate normally distributed with zero expected value and covariance matrix H_t,

$$r_t|\varphi_{t-1} \sim N(0, H_t) \quad (1),$$

$$H_t \equiv D_t R_t D_t \quad (2)$$

where r_t is a $k\times1$ vector; H_t – the conditional covariance matrix; R_t – a $k\times k$ time-varying correlation matrix, and all variable information up to $t-1$ is contained in φ_{t-1}. The logarithmic changes can be either random error process (mean zero) or residuals from a filtered time series, D_t – the $k\times k$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $h_{it}^{1/2}$ as the i-th element of the diagonal. D_t is obtained from the following univariate GARCH specification

$$h_{ii,t} = \omega_{ii} + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q} + \sum_{p=1}^{P_i} \alpha_{ip} r_{iit-p}^2 \quad (3)$$

where ω_{ii} is the constant value; for $i = 1, 2, \ldots., k$ with the usual GARCH restrictions for non-negativity and stationarity of the variances, i. e. non-negativity of the parameters. If these conditions are satisfied, H_t will be positive definite for all

t. Dividing each return by its conditional standard deviation, $h_{it}^{1/2}$, one obtains the vector of standardised returns, $\varepsilon_t = D_t^{-1} r_t$, where $\varepsilon_t \sim N(0, R_t)$. This vector may be used to write the Engle[5] specification of a dynamic correlation structure for the set of returns

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\overline{Q} + \sum_{m=1}^{M} \alpha_m (\varepsilon_{t-m}\varepsilon'_{t-m}) + \sum_{n=1}^{N} \beta_n Q_{t-n} \quad (4)$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (5)$$

where $\overline{Q}$ is the unconditional covariance of the standardised residual resulting from the first stage estimation and Q_t^* – a diagonal matrix composed of the square root of the diagonal elements of Q_t. The empirical estimation of equation (4) proceeds in two steps as suggested by Engle[5]. Initially, the matrix $\overline{Q}$ which denotes correlations between standardised residuals is estimated. In this first step, the long-run correlations are estimated from the unconditional sample correlations. Then, in the second step, $\overline{Q}$ is replaced by the ample counterparts, and the parameters corresponding to the dynamic correlation are estimated.

The elements of R_t will be of the form $\rho_{ijt} = q_{ijt}/(q_{iit}\, q_{jjt})^{1/2}$, where q_{ijt}, q_{iit} and q_{jjt} are the elements of Q_t corresponding to the indices. For R_t to be positive definite the only condition, which needs to be satisfied that Q_t is positive definite (see Engle and Sheppard[6] for details on the condition of R_t). This implies that after a shock occurs, the correlation between two time series will return to the long-run unconditional level. Hence, equation (4) is referred to as a DCC(m, n) model. Engle[5] shows that under the normality assumption of equation (1), the log-likelihood function for the estimation of equation (4) is given by

$$L = -\frac{1}{2}\sum_{i=1}^{T}(k \lg(2\pi) + \lg(|H_t|) + r_t' H_t^{-1} r_t) \quad (6)$$

Substituting equation (2) into equation (6) using $\varepsilon_t = D_t^{-1} r_t$, the simplified log-likelihood function is given by

$$L = -\frac{1}{2}\sum_{t=1}^{T}[k \lg(2\pi) + 2\lg|D_t| + \lg(|R_t|) + \varepsilon_t' R_t^{-1} \varepsilon_t \quad (7)$$

The formulation of the log-likelihood function in equation (7) allows the model to be easily estimated by separating the estimation procedure in a volatility part and a correlation part. The resulting estimates will be consistent but inefficient. The first stage of the estimation process replaces R_t with $k \times k$ identity matrix to get the first stage likelihood. This reduces equation (7) to the sum of the log-likelihoods of univariate GARCH equations. The second stage estimates the DCC parameters in equation (4) using the original likelihood in equation (7) conditional on the first stage univariate parameter estimates. The parameter estimates the two-stage

DCC estimator are consistent and asymptotic normal (see Engle and Sheppard[6] and White[7] for detailed proofs).

EMPIRICAL RESULTS AND DISCUSSION

In this study, annual observations of carbon dioxide emissions volume and real GDP values over the period 1800–2006 were used. Carbon dioxide emissions volume is collected from the Carbon Dioxide Information Analysis Center – CDIAC. The real GDP values are provided by Johnston and Williamson[8]. Data are transformed into percentage changes for calculating growth rates. Table 1 presents some diagnostic statistics for growth series. Carbon dioxide growth series are negatively skewed with excess kurtosis whereas GDP growth series are positively skewed with excess kurtosis. Also the Jarque–Bera test (JB) results indicate that all series are non-normal. *Q*-statistics for both series and squared series show the evidence in favour of first order dependence and second order nonlinear dependence in the data, respectively. Hence, significant conditional heteroscedasticity supports the use of GARCH-type models to capture the time-varying volatility pattern of the growth series. The conventional unit root tests results of the augmented Dickey–Fuller test (ADF) and the Phillips–Perron test (PP) reported in Table 2 reject the null hypothesis indicating that series are stationary. Hence, growth series are appropriate for analysis as expected.

Table 1. Summary statistics

Data	Mean	SD	Skewness	Kurtosis	JB	$Q(10)$	$Q_s(10)$
CO_2^*	0.053	0.082	0.150	4.351	16.436	52.677*	32.415*
GDPgr**	0.038	0.044	–0.265	5.464	54.519	38.978*	75.519*

* CO_2 (thousand metric t of carbon dioxide); ** GDPgr (% Gross Domestic Product growth rate).

Table 2. Unit root test results of series

		ADF	PP
CO_2^*	η_μ	–5.4368(2)*	–14.2674(8)*
	η_τ	–7.1442(2)*	–15.2605(6)*
GDPgr**	η_μ	–10.6246(1)*	–10.1699(14)*
	η_τ	–10.6249(1)*	–10.2102(15)*

Note: η_τ and η_μ refer to the test statistics with and without trend, respectively; *, ** and *** denote rejection of null hypothesis at 1, 5 and 10, respectively; numbers in parentheses are optimum lags determined according to the Akaike Information Criteria and Newey – West Bandwith Criteria for ADF and PP tests, respectively.

Table 3 reports the estimation results of DCC (1,1) model. Sum of $\alpha_{1,I}$ and $\beta_{1,I}$, where $I = CO_2$ and GDP growth, is close to one, which indicates the high persistence in conditional variances. The unconditional correlation is about 0.53, however, the constant correlation test (CC test) of Engle and Sheppard[6] clearly rejects the null of constant correlation, which indicates that conditional models are more appropriate to model the time variant correlation than unconditional correlation measure. The insignificant Ljung–Box statistics reveal that the DCC model adequately captures the conditional heteroscedasticity. Figure 1 shows the conditional correlation between CO_2 and GDP over the period 1800–2006. Conditional correlations are positive and over 0.5 during the sample period, indicating the strong relation between emissions and economic growth. The results indicate that the correlations increased significantly between 1800 and 1850 and decreased between 1850 and 1875. As can be seen in Fig. 1, the correlation has an increasing trend between 1875 and 1925 and relatively stable during 1925–1970. However, volatility in correlation is low in this time period. The correlation is highly volatile during the period 1970–2006.

Table 3. Estimation results of DCC(1,1) models

	DCC-GARCH	
	coefficient	*t*-value
ω_{CO_2}	0.0034	(0.005)
α_{1,CO_2}	0.1721*	(4.817)
β_{1,CO_2}	0.8278*	(18.835)
ω_{GDP}	0.0003	(1.293)
$\alpha_{1,GDP}$	0.1600*	(2.735)
$\beta_{1,GDP}$	0.7528*	(7.027)
Conditional correlation		
α_1^*	0.0138	(0.788)
β_1^*	0.9854*	(37.044)
$\bar{\rho}$	0.5326	
Loglikelihood	591.7079	
CC(5)	19.0785*	
$Q_s(10)$	3.4001	7.5995

Note: the CC test proposed by Engle and Sheppard (2001) finds evidence in favour of a time-varying correlation matrix; *, ** and *** indicate significance levels at 1, 5 and 10%, respectively.

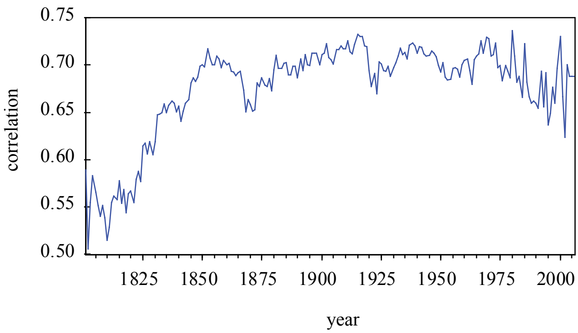

Fig. 1. Correlation between CO_2 and GDP

In this study, the declining trend in correlation in the last couple of decades shows the deceleration of carbon dioxide emissions in the USA as economic growth continues. There are many explanations for this declining trend in the correlation between economic growth and emissions. Beginning with the 1970's, countries have started to pay attention to environmental issues. Concerning climate change, the signing of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 and the Kyoto Protocol[9] in 1997 had been important global actions. Although the USA has not ratified the Kyoto Protocol, investments for a low-carbon future have already taken their way. Most of the big multinational companies as well as some USA states have already taken action in this direction by investing in low-carbon production facilities or decreasing their CO_2 emissions somehow. On the other hand, carbon has already been started to be sold in some of the USA states as well as in international markets serving as a motivator for companies to decrease their carbon emissions.

In parallel with the transition to a low-carbon economy, companies have started to include possible environmental regulations in their strategic plans. The tastes and preferences of the high-income consumers who are most likely to be more sensitive about environmental issues is another factor pushing businesses to pay attention to their carbon dioxide emissions[10]. The fact that fossil fuels are decreasing day by day and that energy efficiency has become an important factor in cost competitiveness have led many companies and countries in the world to consider the sources and utilisation of energy more carefully. In accordance with the new energy policies, countries and companies have started to invest in renewable energy sources and find new ways to save energy. In addition to this, the services sector has developed rapidly over the last couple of decades in many developed countries and especially in the USA which creates less CO_2 emissions.

As economy continues to grow, its marginal cost of reducing carbon dioxide falls. Thus, a larger economy has the chance of operating cleaner and cheaper than a smaller economy[10]. Cleaner technologies also become cheaper as a result of the spread of new technologies. Hence, low-carbon development paths offer the business world new opportunities to exploit for a sustainable and successful future.

CONCLUSIONS

Facing the climate change challenge after the 1970's, the establishment of a low-carbon economy has been championed as a solution to this problem. In a low-carbon economy, economic growth continues with decreasing carbon dioxide emissions, reversing the historical relationship. Especially after 1990's, with the support of international agreements, engagement of the business world, increasing awareness, the new structure of the competitive world markets and the demand for new energy sources, companies and countries have started to give importance to low-carbon investments and activities. Therefore, although economic growth continues, presently, its correlation with carbon dioxide emissions has started to decline in some countries. In parallel with all these, this research has shown that starting with the 1970s, the emissions of the USA has slowed down although economic growth has continued and hence, emphasised the changing correlation between economic growth and emissions. Besides, the results of this research also support this changing correlation with the expectation that further acceleration in economic development might be coupled with a further slowdown of carbon dioxide emissions reversing the historical relationship in the coming years.

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