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The Volatility Assessment of CO_2 Emissions in Uzbekistan: ARCH/GARCH Models

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ABSTRACT

The study is a pioneer in investigating the volatility of CO_2 emissions in Uzbekistan. To this end, Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are used spanning the period 1925-2021 for the annual data of CO_2 emissions. The results indicate that ARCH model is more adequate than GARCH model in the volatility assessment. Furthermore, it is found that the volatility of CO_2 emissions in Uzbekistan is very high. The policymakers have to consider the high volatility of CO_2 emissions in the environmental policy measures dedicated to reduce carbon dioxide emissions.

Keywords: CO_2 Emissions, Volatility, ARCH, GARCH, Uzbekistan

JEL Classi ications: C22, C5, Q53, Q58

1. INTRODUCTION

The economy of Uzbekistan highly depends on fossil fuel energy, like other Central Asian countries. More specifically, fossil fuel-related energy consumption share is counted as 97.35% of total energy consumption in 2021 (Our World in Data, 2023). Consequently, carbon dioxide emissions are high in the country.

Uzbekistan is obliged to comply with the Paris Climate Agreement's goals and take actions towards achieving a carbon-neutral nation. In accordance with the Paris Climate Agreement, Uzbekistan must reduce greenhouse gas emissions per unit of GDP by 35% of 2010 levels by 2030, compared to the 10% decrease agreed in the first Nationally Determined Contribution (NDCs) agreement. Furthermore, achieving this objective is related to Uzbekistan's pledge to the attainment of a 'green economy' over the period 2019-2030 and the 16 Sustainable Development Goals (SDGs) (United Nations, 2022). To carry out the enactment of these international environmental agreements, Uzbekistan should implement effective policies to reduce carbon emissions.

In recent years, the strand of research has included much work that examines the relation between CO_2 emissions and the influence of its determinants. Among these studies, Uzbekistan is either included in panel studies (Salahodjaev et al., 2021; Saidmamatov et al., 2023) or solely (Apergis et al. (2023) analyzed. The limitation of these studies is that they do not allow assessing environmental risk emerged from CO_2 emissions. Risk assessment is important to reduce CO_2 emissions since environmental issues represent a dynamic character, and it is not clear what path they follow. Given this fact, this study uses Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to investigate the volatility of CO_2 emissions in Uzbekistan.

2. LITERATURE REVIEW

2.1. The Studies of CO_2 Emissions in Uzbekistan

In the literature, CO_2 emissions are mostly examined depending on other variables using panel methods. Among panel methods, the works by Zhang (2019), Hongxing et al. (2021), Salahodjaev et al. (2021), Apergis and Payne (2010), Rasoulinezhad and Saboori (2018), Masron and Subramaniam (2018) and Saidmamatov et al. (2023) can be provided. More specifically, Apergis and Payne (2010) employ a vector error correction methodology for a group of countries of the Commonwealth of Independent States (CIS) over the period 1992-2004. They note that energy consumption has a statistically significant, positive impact on CO_2 emissions in the long run and that real output exhibits an inverted U-shaped pattern, supporting the Environmental Kuznets Curve (EKC) hypothesis. Rasoulinezhad and Saboori (2018), in an empirical study of the long run and causal linkages between CO_2 emissions, economic growth, and renewable and fossil fuels energy for a group of the CIS countries, including Uzbekistan, observe a bi-directional long-run relationship across all variables and in all countries, except for the association between economic growth and renewable energy. Masron and Subramaniam (2018) examine the direct and indirect impact of corruption on environmental deterioration in a panel of 64 developing countries, including Uzbekistan. Saidmamatov et al. (2023) examine economic growth, energy consumption, agriculture and irrigation water consumption and agriculture productivity on environmental pollution in five countries of Central Asian countries where Uzbekistan is included, by applying panel data models, namely the Panel FMOLS, Panel DOLS and Panel ARDL-PMG approaches over the period 1992-2020. Their results indicate that there is a positive long-term impact of economic growth, water productivity, energy consumption and electricity production on CO_2 emissions, while agriculture value added and trade openness have a negative and statistically significant influence on CO_2 emissions in Central Asia.

There is only a single paper by Apergis et al. (2023), which employs the time series ARDL model to investigate the impact of renewable and fossil fuel energy consumption on CO_2 emissions in Uzbekistan during the period 1985-2020. They find that the main contributors to CO_2 emissions are fossil fuel energy consumptions whereas renewable energy consumption negatively impacts on CO_2 emissions.

It should be noted that there is no single study which examines the volatility of CO_2 emissions in the case of Uzbekistan employing ARCH/GARCH models.

2.2. ARCH/GARCH Models for Examining CO_2 Emissions

The use of CO_2 emissions in autoregressive moving average and autoregressive conditional heteroscedasticity models for estimation and forecasting purposes is gaining popularity in the literature. More specifically, Lotfalipour et al. (2013) predicted CO_2 emissions in Iran over the period 1965-2010 based on Grey System and Autoregressive Integrated Moving Average. Comparing these two methods, they find that Grey system forecasting is more accurate than the other. Dutta et al. (2018), employing the bivariate VAR-GARCH approach, investigated the link between the carbon emission market and the market of clean energy stocks (daily return and volatility linkages between the European Union Allowance (EUA) prices and clean energy stock returns). Their findings indicate a significant volatility linkage between emissions and European clean energy price indexes. Benz and Truck (2009) analyze the short-term spot price behavior of carbon dioxide (CO_2) emission allowances of the new EU-wide CO_2 emissions trading system (EU ETS) using AR–GARCH model. Their findings strongly support the adequacy of the model capturing characteristics like skewness, excess kurtosis and, in particular, different phases of volatility behavior in the returns. Byun and Cho (2013) examine the volatility forecasting abilities applying GARCH-type model using carbon futures prices. Due to their results, Brent oil, coal, and electricity may be used to forecast the volatility of carbon futures. Dritsaki and Dritsaki (2020) investigate CO_2 emissions in the EU-28. They employ the ARIMA(1,1,1)-ARCH(1) model and a dynamic process as well for forecasting. Comparing the results, they find that the static procedure (ACH) provides a better forecast compared to the dynamic one (GARCH).

Given the literature review provided above, the motivation emerges to empirically assess the volatility of CO_2 emissions in Uzbekistan using ARCH/GARCH models.

3. DATA AND METHODOLOGY

To study the volatility of carbon dioxide emissions in Uzbekistan, annual data of CO_2 emissions, measured in millions of tons, is used spanning 1925-2021. The data is downloaded from Our World in Data (https://ourworldindata.org/co2/country/uzbekistan).

To estimate volatility of CO_2 emissions in the case of Uzbekistan, we employ ARCH (Autoregressive Conditional Heteroskedasticity (Engle, 1982) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Bollerslev, 1986) models. An ARCH model is an econometric model for the variance of a time series. Engle (1982) used this model to estimate the means and variances of inflation in the U.K. Recently, ARCH model is applied to examine the volatility of environmental factors (Sudha, 2015). This gives us the motivation to further employ ARCH model for environmental variables. Moreover, we use annual data in the analysis similarly to Narayan et al. (2018) for ARCH model. Furthermore, Engle (1982) did not point out any restrictions regarding the data and fields for ARCH models. Later Bollerslev (1986) extended ARCH model (Equation 2) to GARCH model (Equation 3).

In order to build ARCH/GARCH models, there should be a presence of ARMA (Autoregressive Moving Average) (Box and Jenkins, 1970) process whose specification can be described as:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \ldots + \varphi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \quad (1)$$

where, y is dependent variable, p is autoregressive terms, φ_0 is constant, $\varphi_1, \ldots \varphi_p$ – the coefficients of autoregressive component, ε_t – error term, q is moving average terms, $\theta_1, \ldots \theta_q$ - the coefficients of moving average component.

After verifying both AR and MA process, the ARMA specification should be tested for heteroskedasticity (Breusch and Pagan, 1979). If heteroskedasticity exists in ARMA model, ARCH (Equation 2) and GARCH (Equation 3) models can be developed, which have the following specifications:

$$\sigma_t'^2 = \alpha_0' + \alpha_1' \varepsilon_{t-1}'^2 + \alpha_2' \varepsilon_{t-2}'^2 + \ldots + \alpha_n' \varepsilon_{t-n}'^2 \tag{2}$$

$$\hat{\sigma}_t^2 = \hat{\alpha}_0 + \hat{\alpha}_1\hat{\varepsilon}_{t-1}^2 + \hat{\alpha}_2\hat{\varepsilon}_{t-2}^2 + \ldots + \hat{\alpha}_j\hat{\varepsilon}_{t-j}^2 + \hat{\beta}_1\hat{\sigma}_{t-1}^2 + \hat{\beta}_2\hat{\sigma}_{t-2}^2 + \ldots + \hat{\beta}_m\hat{\sigma}_{t-m}^2 \tag{3}$$

$\sigma_t'^2, \hat{\sigma}_t^2$ – conditional variance, ε' and $\hat{\varepsilon}$ are error terms, a', $\hat{a}$ and $\hat{\beta}$ are the coefficients of volatility, n, j and m are lag orders, $\alpha_0', \alpha_1', \ldots, \alpha_n' > 0, \hat{\alpha}_0, \hat{\alpha}_1, \ldots, \hat{\alpha}_j > 0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_m \geq 0, n \geq 0, j \geq 0,$ $m \geq 0, 0 \leq \alpha_0' + \alpha_1' + \ldots + \alpha_q' < 1,$ $\hat{\alpha}_0 + \hat{\alpha}_1 + \ldots + \hat{\alpha}_j + \hat{\beta}_1 + \hat{\beta}_2 + \ldots + \hat{\beta}_m < 1$.

The data is transformed into the natural logarithm. Moreover, the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips-Perron (PP) test (Phillips and Perron, 1988) unit root tests are performed to check the stationarity, which is a crucial aspect of building ARMA and ARCH/GARCH models.

As a diagnostics for the developed ARCH model, ARCH/GARCH LM test for heteroskedasticity (Breusch and Pagan, 1979) is conducted, which must not exist.

Table 1: Unit root tests

	ADF		PP	
	Level	**1st dif.**	**Level**	**1st fid.**
$LOGCO_2$	0.58	0.00	0.20	0.00

Source: Authors' estimations. For the ADF, the P values are reported, obtained with a specification adopting an automatic selection of BIC information criterion and including trend and intercept. Maximum lags are set to 2 because of annual data. For the PP test, the P values are reported, which are obtained with a specification adopting an automatic selection of Newey-West Bandwidth, including trend and intercept. The null hypothesis for ADF and PP tests is the presence of the unit root. The null hypothesis is rejected when P<0.05

4. RESULTS

Before estimating volatility, the data, used in natural logarithm form, is checked for unit root test. To this end, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests are employed. The results are reported in Table 1.

According to Table 1, CO_2 emissions are stationary in the first difference. Given this evidence, the next step is to identify ARIMA (p, d, q) model for emission. To this end, the correlogram for emissions is provided in the first differences (Table 2).

Table 2 shows the existence of ARIMA process for CO_2 emissions (*$logCO_2$*). From ACF, it can be seen that lag order for MA process is 1. Due to PACF, the probable lag order for AR process might be in the length [1;3]. The final ARIMA (p,d,q) model is defined based on AIC, BIC and HQ criterion.

Table 3 expresses the estimated ARIMA models with possible lag length based on Table 2. It can be noted that Model 2 is adequate in comparison with Model 1 and Model 3. More specifically, all the coefficients, both AR and MA processes, are statistically significant. Furthermore, the AIC, BIC and HQ values of Model 2 are lower than the other models (Model 1 and 3). Given this fact, we consider ARIMA (2,1,1) model to estimate ARCH/GARCH models.

In order to estimate ARCH/GARCH models, ARIMA (2,1,1) model should have heteroskedasticity. According to heteroskedasticity test, the null hypothesis is no existing ARCH/GARCH effects up to the specified lag, whereas the alternative hypothesis means there are ARCH/GARCH effects up to the specified lag. The null hypothesis is rejected if P-value of Chi-square is lower than 0.05 (P<0.05). Due to Appendix 1, there is a presence of heteroskedasticity in ARIMA (2,1,1) model. Given this evidence, ARCH/GARCH models can be built, however the lag order of ARCH model should be selected based on PACF from the correlogram of squared residuals whereas the lag order

Table 2: Autocorrelation and partial autocorrelation of CO_2 emissions (*$logCO_2$*) in the first difference

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.292	0.292	8.5287	0.003
*|. |	**|. |	2	−0.126	−0.231	10.137	0.006
.|* |	.|** |	3	0.158	0.313	12.691	0.005
.|** |	.|* |	4	0.270	0.086	20.237	0.000
.|* |	.|. |	5	0.090	0.051	21.078	0.001
.|* |	.|* |	6	0.074	0.096	21.663	0.001
.|. |	*|. |	7	−0.002	−0.150	21.663	0.003
.|. |	.|* |	8	0.024	0.077	21.728	0.005
.|. |	.|. |	9	0.056	−0.061	22.070	0.009
.|* |	.|* |	10	0.108	0.133	23.360	0.009
.|. |	*|. |	11	−0.043	−0.139	23.564	0.015
*|. |	.|. |	12	−0.098	−0.015	24.644	0.017
.|. |	.|* |	13	0.070	0.084	25.200	0.022
.|* |	.|. |	14	0.137	0.018	27.359	0.017
*|. |	*|. |	15	−0.101	−0.090	28.546	0.018
*|. |	.|. |	16	−0.115	−0.028	30.122	0.017
.|* |	.|* |	17	0.151	0.182	32.875	0.012
.|* |	.|. |	18	0.178	0.030	36.722	0.006
.|* |	.|* |	19	0.101	0.195	37.988	0.006
.|* |	.|. |	20	0.119	0.042	39.746	0.005

Figure 1: The graphs of actual value and volatility spillover of CO_2 emissions in Uzbekistan over the period 1925-2021

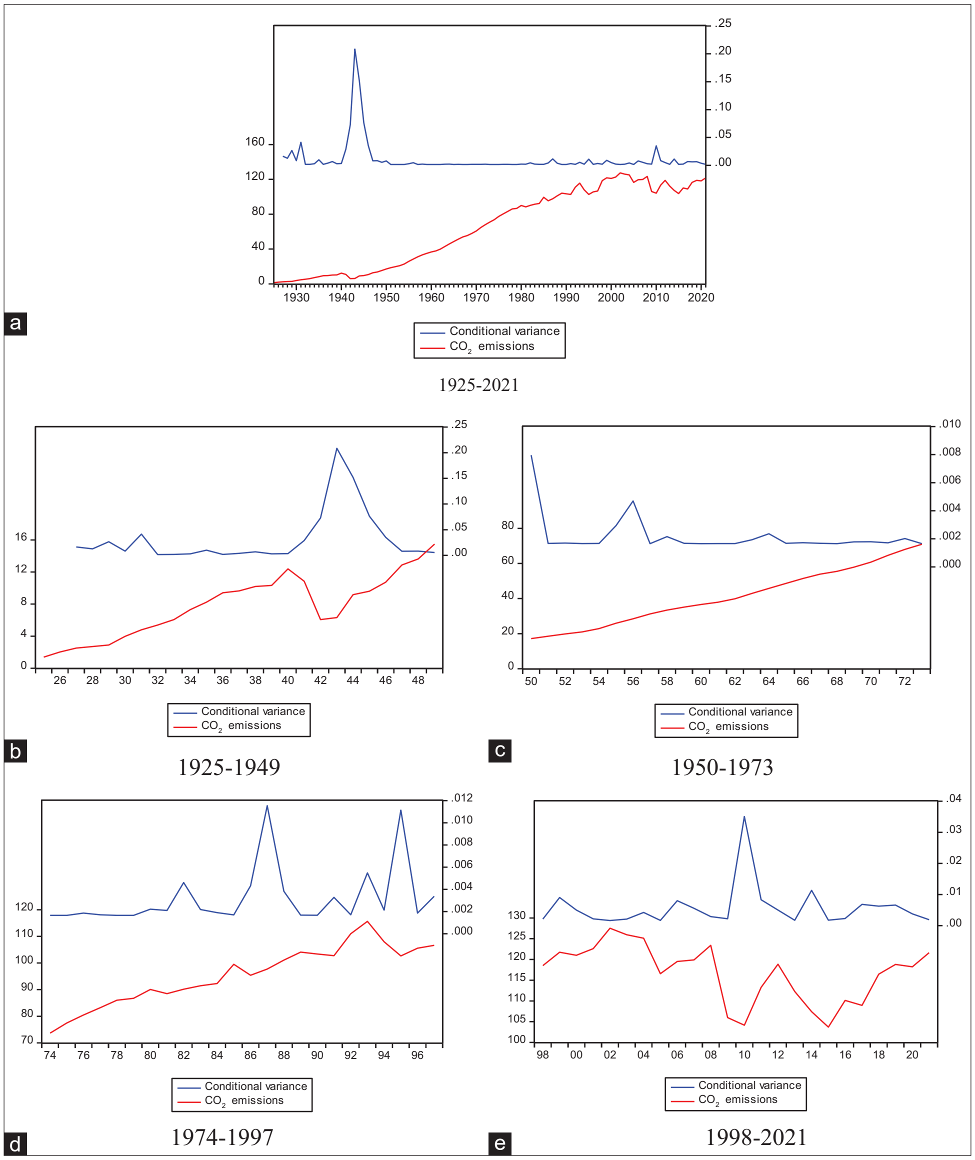

Table 3: The estimated ARIMA (p, d, q) models for CO_2 emissions ($logCO_2$) and AIC, SIC and HQ test results

Coefficients	Model 1: ARIMA (1,1,1)	Model 2: ARIMA (2,1,1)	Model 3: ARIMA (3,1,1)
AR	0.04 (0.28)	−0.21 (0.01)**	0.13 (0.22)
MA	0.61 (0.00)***	0.45 (0.00)***	0.48 (0.00)***
Constant	0.04 (0.00)***	0.04 (0.00)***	0.04 (0.01)**
AIC	−1.80	−1.83	−1.80
BIC	−1.69	−1.72	−1.70
HQ	−1.76	−1.78	−1.76

P-values are in parentheses. Asterisks represent statistical significance *** and ** for 1% and 5% levels, respectively. AIC, BIC and HQ denotes Akaike, Schwartz and Hannan-Quinn information criterion, respectively

for GARCH model is considered from ACF of ARIMA (2,1,1) model.

From Table 4, it can be clearly seen that the lag order for ARCH model is 1. Due to this fact, we proceed in the estimation of ARCH (1) model. Moreover, according to ACF, the GARCH effect (GARCH (1,1)) can be estimated with lag order 1.

Table 5 shows the mean and variance equations for employed ARCH (1) and GARCH (1,1) models. All coefficients of both mean and variance equations for ARCH (1) model is statistically significant. Furthermore, the coefficients of constant and lagged squared residual ($\varepsilon'^2(-1)$) in the variance equation are positive, and the coefficient of squared residual $\varepsilon'^2(-1)$ is <1, and there is no heteroscedasticity according to the LM-test result (P=0.65).

The coefficients of mean and variance equations in GARCH (1,1) model are statistically significant and variance equation coefficients are positive. However, the sum of the coefficient of

Table 4: The correlogram of squared residuals of ARIMA (2,1,1) model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.266	0.266	7.1023	0.008
.|* |	.|. |	2	0.131	0.065	8.8461	0.012
.|. |	*|. |	3	−0.016	−0.072	8.8734	0.031
.|* |	.|* |	4	0.162	0.189	11.577	0.021
.|. |	*|. |	5	−0.015	−0.103	11.600	0.041
.|. |	.|. |	6	0.028	0.024	11.684	0.069
.|. |	.|. |	7	−0.000	0.025	11.684	0.111
.|. |	.|. |	8	0.046	−0.004	11.910	0.155
.|. |	.|. |	9	−0.025	−0.018	11.979	0.215
.|. |	.|. |	10	0.032	0.037	12.095	0.279
.|. |	.|. |	11	0.014	0.004	12.118	0.355
.|* |	.|* |	12	0.177	0.174	15.669	0.207
.|. |	*|. |	13	−0.005	−0.098	15.672	0.267
.|. |	.|. |	14	0.021	0.005	15.722	0.331
.|. |	.|* |	15	0.055	0.105	16.076	0.377
.|** |	.|** |	16	0.292	0.213	26.196	0.051
.|. |	*|. |	17	0.004	−0.140	26.198	0.071
.|. |	.|. |	18	−0.012	−0.028	26.216	0.095
.|. |	.|. |	19	−0.009	0.046	26.226	0.124
.|. |	*|. |	20	0.006	−0.107	26.230	0.158

Table 5: The estimated ARCH (1) and GARCH (1,1) models

Coefficients	Model 1: ARCH (1)	Model 2: GARCH (1,1)
	Mean equation	
AR (2)	0.37 (0.00)***	0.32 (0.01)**
MA (1)	0.70 (0.00)***	0.69 (0.00)***
Constant	0.03 (0.00)***	0.04 (0.00)***
	Variance equation	
Constant	0.00 (0.00)***	0.00 (0.18)
$\varepsilon^2(-1)$	0.91 (0.01)**	
$\varepsilon^2(-1)$		0.82 (0.00)***
$\sigma^2(-1)$		0.47 (0.00)***
LM-test for heteroscedasticity: P value of Chi-square	(0.65)	(0.60)

P-values are in parentheses. Asterisks represent statistical significance * and ** for 1% and 5% levels, respectively**

lagged squared residual and lagged squared variance exceeds 1, which is unacceptable.

On this reason, the developed GARCH (1,1) model is not adequate, and we rely on ARCH (1) model in order to estimate the volatility of CO_2 emissions in Uzbekistan. More specifically, the coefficient of volatility of CO_2 emissions in Uzbekistan is equal to 0.91 due to ARCH (1) model. This could give us an assumption that the volatility of CO_2 emissions of Uzbekistan is very high (Figure 1).

5. CONCLUSION

Even though several studies in literature analyse the relationbetween CO_2 emissions and other factors with panel or time series methods, including Uzbekistan, it is crucial to assess the volatility of CO_2 emissions. Because it allows estimating environmental risk associated with carbon dioxide emissions. To fill this research gap, this study employs ARCH/GARCH models to examine CO_2 volatility. The former model shows more robustness than the latter, which is a consistent result with Dritsaki and Dritsaki (2020). According to the results, the volatility of CO_2 emissions is very high in Uzbekistan (B, C, D, E). Given this evidence, environmental policy makers should implement policy implications considering increasing high volatility.

Any limitation of the research might be the lack of studying volatility linkages between CO_2 emissions and other factors using MGARCH (multivariate Generalized Autoregressive Conditional Heteroskedasticity) model. This gap would serve as an agenda for future works in the field.

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APPENDIXES

Appendix 1

Heteroskedasticity Test: ARCH				
F-statistic	7.195063	Prob. F (1,94)		0.0086
Obs*R-squared	6.825689	Prob. Chi-Square (1)		0.0090
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample (adjusted): 1926 2021				
Included observations: 96 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.006351	0.002858	2.222033	0.0287
RESID^2(-1)	0.266715	0.099433	2.682361	0.0086
R-squared	0.071101	Mean dependent var		0.008671
Adjusted R-squared	0.061219	S.D. dependent var		0.027550
S.E. of regression	0.026694	Akaike info criterion		−4.388175
Sum squared resid	0.066979	Schwarz criterion		−4.334751
Log likelihood	212.6324	Hannan-Quinn criter.		−4.366581
F-statistic	7.195063	Durbin-Watson stat		1.876815
Prob (F-statistic)	0.008637			