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# Variability in Coal Prices: Evidence from the U.S.

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**Variability in Coal Prices: Evidence from the U.S.**

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**Abstract**

Monthly U.S. coal price time series data are tested to determine the persistence of shocks. The time series is then disaggregated by length of agreement to further explore the first and second moments of pricing behaviour. Results show that prices have a variance that changes over time and tend to be highly persistent. Prices from long-term transaction agreements tend to require more lags and have a higher degree of persistence.

**Key Words:** coal prices, variability, persistence and randomness

**JEL:** C22, C51, Q31, Q41

## 1. Introduction

Coal is a prime energy source for the production of electricity in the US and many other countries. Further, electricity is an input into the production of many goods and services. Thus, an understanding of the evolution of coal prices is relevant for many planning and forecasting models. In addition, the evolution of coal prices has important implication for energy policy. US coal supply and demand is driven largely by domestic forces, compared to crude oil, whose supply may be susceptible to exogenous shocks such as unrest in Arab nations coupled with fluctuations in output brought about by OPECs activities. Further, the pricing and trading of coal occur differently from other energy sources due to its form (solid versus liquid) and distribution throughout the world. We therefore expect coal prices to depict different time series patterns from other sources of energy

An analysis of the time series properties of U.S. coal prices is undertaken here. Monthly aggregate data and a disaggregation of the data are analyzed to determine the process by which prices evolve. The disaggregation is prices in coal contracts (agreements greater than one year or greater) relative to spot prices (agreements less than one year).

Coal has supplied roughly 20% of the US primary energy and 50% of US electricity generation for the last 25 years. A stylised fact of the US coal market is that nearly all the coal consumed is produced domestically, with little imports or exports (Energy Information Administration, 2007). Coal-fired power plants currently consume 91% of all coal mined in the U.S., steadily increasing from 70% in 1972 (Energy Information Administration, 2005). The US imports are small, but increasing percentage of its coal. Until the year 2000, the percentage of coal imported was less than 1% and it has risen to 3% in 2007. In response to the large increase in oil prices in the 1970's, the U.S. government initiated subsidizes to the production of coal-fired power plants. As a result, energy use from coal increased from 17% of total U.S. energy use in 1972 to 22% in 2000 (Energy Information Administration, 2006).

Coal contracts are the common form of procurement in the US. The use of the spot market has been increasing since the late-1980s and is roughly 20% of all transactions throughout the 1990s. At the same time, the average duration of contracts has fallen, from 14 years to 8 years (Lange and Bellas, 2007). Contracts are generally between a mine, coal-fired power plant, and a transportation firm (often railroad). The contracts contain many characteristics such as a specified price adjustment mechanism and minimum quantity and coal attribute provisions. Joskow (1985) provides a detailed overview of contracts in the coal industry and notes that a mine and a power plant usually rely on long-term contracts that are incomplete but quite complex. Such contracts contain both price and non-price provisions that serve to prevent both parties from breach. Joskow (1988 and 1990) finds that the price provisions stipulated in contracts were largely adhered to despite the downturn in the market for coal that occurred post-1982. He concludes that in a long-term contract, mines and plants preferred abiding by the contractual obligations to renegotiation, breach of contract or costly litigation. As a result, we expect prices to be less variable for contract transactions (relative to spot) though the persistance of shocks may be higher if they are encorporated into the provisions of the contract.

In spite of the fact that coal play an important role in the US and indeed the industrialised economy energy mix, there is a surprising lack of research into the time series properties of coal prices, especially relative to the research done regarding the evolution of petroleum prices and other sources of energy. Ellerman (1995) discusses the world coal market and concludes that the US is the residual supplier and that changes in productivity drive coal prices. Humphreys (1995) argues that the coal market could be described as interlocking regional market and that Australia is more relevant to world prices than the U.S. Pindyck (1999) uses annual data from 1870-1996 to determine the time series properties of coal (as well as oil and natural gas) prices. Pindyck (1999) argues that the price series should have a stochastic trend line as they should reflect the marginal cost of extraction, which varies with new discoveries and changes in technology. Bachmeier and Griffin (2006) test for integration of the US coal market using spot prices from 1990-2004. They find weak evidence of market integration. Warrell (2006) tests for evidence of market integration in coal using a sample of European and Japan prices over the sample period 1980-2000. Mixed evidence is found of an international market for coal with the entire sample suggesting one market while the sub-sample of the 1990s behaves more regional than international.

There is a good deal of literature on the time series properties of oil prices. For instance, economic theory suggests that oil shocks lead to higher inflation, a contraction in output, and higher unemployment in the short run. It is the rise in energy prices, rather than “high” energy prices that causes these macroeconomic problem, see Kilian (2208), Jones et al (2004), Hamilton (1983), Darby (1982) for empirical evidence. More recently, the literature has focussed on the relationship between oil prices and stock returns. If high oil prices depress real output, then increases in oil price depress aggregate stock prices by lowering expected earnings. Sadorsky (1999) concludes that changes in oil prices impact economic activity but, changes in economic activity have little impact in oil prices. Jones and Kaul (1996) argue that changes in oil prices granger precede most economic series, have an effect on output and real stock returns in the United States.

## 2. Coal price data

Data on coal prices comes from the Federal Energy Regulatory Commission's Form 423 survey. It contains monthly plant level observations of coal transactions for all power plants greater than 50MW capacity. Information on the quality, quantity, price and type of transaction is given for each observation. The prices are for delivered coal, thus they include the transportation costs. The time series analyzed here runs from July 1972-December 2002, 366 observations. The prices are real cents per million British Thermal Units (mm Btu), discounted by the Consumer Price Index (CPI). The CPI data is the monthly consumer price index from the International Monetary Fund's (IMF) online edition of the International Finance Statistics (IFS).

The time series was created by averaging the price in all relevant transactions in a given month. An aggregate time series (all transactions) and a disaggregation are analyzed here. The first disaggregation is by transaction type, contract or spot. A contract transaction is any transaction from an agreement of one year or over in duration, spot transactions are for agreements of less than one year in duration. The coal price series for the sample period July 1972 to December 2002. Average coal prices for the aggregate, contract, and spot series during the sample are $2.21, $2.26, and \$2.12 respectively. The standard deviations during the sample are \$0.76, \$0.85, and \$0.76 respectively. Statistical evidence however, indicates that whereas contract is negatively skewed, spot prices are positively skewed.

Figure 1 gives the aggregate time series and the contract and spot disaggregation series. There is a positive price shock in the mid-1970s corresponding to a large decrease in labour productivity and another small shock in the 1979/1980. From 1980 until 2002, the real price falls at a steady rate until a small increase in the year 2002.

### 3. Model

Let $p_t$ be coal prices, a simple AR (*p*) model is specified as

$$\phi_p(L)p_t = \varepsilon_t \tag{1}$$

where the AR (*p*) polynomial in $L$ of order $P$ is $\phi_p(L) = 1 - \phi_1 L - ... - \phi_p L\varepsilon^p$ and $\varepsilon_t$ satisfies the white noise properties $E[\varepsilon_t] = 0$, $E[\varepsilon_t^{\,2}] = \sigma^2$ and $E[\varepsilon_t \varepsilon_s] = 0 \;\forall s \neq t$.

To check the whiteness of the residuals of (1) we apply a modified version of the Brock, Dechert and Scheinkman (1987) test, BDS for short. We conjecture that nonlinearities in coal prices will be important in examining the particular time series models that fit the data. Further, nonlinearities bear a close affinity with the concept of efficiency of the coal market, where if coal prices are efficient, then current coal prices should contain no information in predicting future coal prices. Given the importance of coal as a source of energy, such predictability will have important implication for the demand for, and supply of coal, and the pricing policy as well as regulation of the US coal market.

To model variability we employ GARCH models (see Bollerslev *et al*, 1992 for a survey). Given (1) as the mean equation we specify the variance equation as

$$\sigma_t^{\ 2} = \alpha_0 + \alpha_1 \varepsilon^2_{\ t-1} + \beta_1 \sigma^2_{\ t-1} \qquad (2)$$

where $\sigma_t^{\ 2}$ is the conditional variance. The $\alpha_1$ models the short-run persistence of shocks in coal prices while $\beta_1$ represent long-run persistence. The parameters $\alpha(\mathrm{L}) = \alpha_1 \mathrm{L} + \ldots \alpha_q \mathrm{L}^q$ and $\beta(\mathrm{L}) = \beta_1 \mathrm{L} + \ldots + \beta_p \mathrm{L}^p$ are equivalent to an ARMA (p, q) if all the roots of $1 - \beta(\mathrm{L})$ lie outside the unit circle. The conditional variance must be non-negative. This necessitates the following restrictions on the parameters: $\omega > 0$, $\alpha_1 > 0$ and $\beta_1 \geq 0$.

We also account for asymmetries (Black 1976, Christie 1982) by fitting GJR-M (or

Threshold GARCH, TGARCH)

$$\sigma_t^{\ 2} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^{\ \ 2} + \beta_1 \sigma^2_{\ t-1} + \gamma_1 \varepsilon_{t-1}^{\ \ 2} N_{t-1} \qquad (3)$$

$N_{t-1}$ is an indicator for negative $\varepsilon_{t-1}$ i.e. $N_{t-1}$=1 if $\varepsilon_{t-1}$<0 and $N_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$ and $\alpha_1$, $\beta_1$ and $\gamma_1$ are non-negative parameters satisfying conditions similar to those of the GARCH in {2}. From {3}, a positive $\varepsilon_{t-1}$ contributes $\alpha_1 \varepsilon_{t-1}^{\ \ 2}$ to $\sigma_t^{\ 2}$, whereas a negative $\varepsilon_{t-1}$ has a larger impact $(\alpha_1 + \gamma_1)\varepsilon_{t-1}^{\ \ 2}$ with $\gamma_1$ >1. Finally an EGARCH is fit as

$$\ln(h_t) = \alpha_0 + \alpha_1 z_{t-1} + \gamma_1\left(\left|z_{t-1}\right| - E\left(\left|z_{t-1}\right|\right)\right) + \beta_1 \ln(h_{t-1}) \tag{4}$$

The natural log formulation ensures positive variances, thus dispensing with the need for parameter restrictions. Secondly, volatility at time *t* depends on both the size and sign of the normalized errors (see Nelson, 1991).

### 3.1. Time series patterns of coal prices

We first examine the behaviour of coal prices over the period 1972 to 2002 as shown in Figure 1. The graph in Figure 1 seems to be mean reverting although this is at different speeds. Given this behaviour of coal prices, it is plausible that the true data generating process for coal prices contains one or more unit roots. One immediate (and perhaps inappropriate) method to think of unit root would be to examine the autocorrelation function (acf) of coal prices. However, although shocks to a unit root process will remain in the system indefinitely, the acf for a unit root process (a random walk) will often be seen to decay away very slowly to zero. Thus such a process may be mistaken for a highly persistent but stationary process. Based on Figure 1 we test for random walks in coal prices using the Augmented Dickey Fuller test.

**Table 1: ADF test**

| **Contract** | | **Spot** | | **Aggregate** | |
|---|---|---|---|---|---|
| **Levels** | **First Diff** | **Levels** | **First Diff** | **Levels** | **First Diff** |
| -0.506 | -3.272 | -1.379 | -5.429 | -1.005 | -9.275 |

Note: Critical values at the 5% level= -2.869. Maximum lag chosen is 12 based on Schwartz Criterion

In Table 1, the unit root cannot be rejected for any of the disaggregated coal prices. Traditional unit root tests such as the ADF suffer from low power and may not be very informative of the time series patterns of coal prices. To gain further insight we extend the analysis by fitting a general autoregressive model in the price series and examine whether there is evidence of randomness and nonlinearities. The strategic interaction among coal market participants, demand and supply factors and coupled with the dynamics of economy-wide fluctuations may introduced nonlinearities in coal prices. The BDS test based on range (see Kočenda 2001 and Kočenda and Briatka, 2005) is applied here. This test overcomes the problem of selecting embedding dimensions and the proximity parameter inherent in traditional BDS test of Brock et al (1996, 1997). The range is selected through integration across the correlation integral, thereby avoiding the arbitrary selection of epsilon. We fit (1) in the disaggregated coal prices to pre-whiten the data. This way we make sure that the rejection of the null hypothesis of pure noise is due only to significant nonlinearity. Therefore, we determine the pre-whitening AR (*p*) for values of *p* from *0* (regress on a constant) up to *10* lags and the one with the minimum Schwartz Criterion is chosen. Table 2 display the results of the AR (*p*) model selected on the basis of information criteria for each of the disaggregated coal prices.

**Table 2: AR (*p*) Model**

| | **Contract** | **Spot** | **Aggregate** |
|---|---|---|---|
| $u$ | -0.0008(-0.44) | -0.0007(-0.24) | -0.0008(-0.3102) |
| $\phi_1$ | 0.222***(4.388) | 0.575***(13.37) | 0.616**(2.798) |
| $\phi_2$ | 0.132**(2.578) | | |
| $\phi_3$ | 0.296***(5.87) | | |
| $\phi_4$ | | | |
| $\phi_5$ | | | |
| **BG(5)** | 1.858[0.1009] | 1.019[0.405] | 3.421[0.000] |
| **DW** | 1.95 | 2.04 | 1.85 |
| **ARCH(10)** | 6.308[0.000] | 4.506[0.000] | 12.622[0.000] |

The evidence from Table 2 that Contract coal prices should be modelled with a higher order AR model is not surprising given the common use of pre-specified price adjustment mechanisms. With the exception of the Contract series, the Aggregate and Spot series are best modelled by assuming shorter lags. Whereas Table 2 indicates that there is no first order serial correlation in the data, significant ARCH effects can be detected in all coal series, indicating that ARCH models could well approximate the data generating process. Beside the presence of ARCH effects, one would like to see whether any further structure remains in the data. For instance if the AR (p) model is able to explain the behaviour of coal prices, we expect the residuals to be independently and identically distributed. We save the residuals of the best linear AR (*p*) model and test the residuals for any remaining serial dependence. Our next step is to use the residuals of the AR ($p$) regression to compute the BDS test statistics for nonlinearity. The results are summarised in Table 3.

**Table 3: BDS test for Randomness**

| | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ | $\beta_6$ | $\beta_7$ | $\beta_8$ | $\beta_9$ | $\beta_{10}$ |
|---|---|---|---|---|---|---|---|---|---|
| **Contract** | 1.356 | 1.965 | 2.533 | 3.112 | 3.682 | 4.256 | 4.804 | 5.35 | 5.639 |
| **Spot** | 0.994 | 1.413 | 1.837 | 2.245 | 2.669 | 3.102 | 3.522 | 3.931 | 4.35 |
| **Aggregate** | 0.286 | 0.396 | 0.487 | 0.571 | 0.656 | 0.743 | 0.829 | 0.915 | 1.002 |

Notes: All the computed test statistics from the Kočenda(2000) and Kočenda and Briatka (2005) BDS test using the optimal range of ($0.60\sigma$ , $1.90\sigma$ ) with a bootstrap sample of 2500 were rejected at the 1% significance level. Computations were done using K2K software

In Table 3 we compute the BDS statistic in such a way as to rule out the narrowest null of exact linearity. We choose the optimal range to be ($0.60\sigma$, $1.90\sigma$) as suggested by Kočenda (2001) and Kočenda and Briatka (2005)[1] . Belaire-Franch (2003) show that if there is excess kurtosis in the data, the assumption of independent and identical distribution (iid) of the error term would be erroneously rejected by the test frequently. Also since, the BDS is nonparametric, there is a strong case for bootstrapping. Therefore, 2500 new samples were independently drawn from the empirical distribution of the pre-whitened data. All the computed BDS statistics rejects the null at 1%. However, rejection of the null under BDS is not informative regarding the type of nonlinearity that is present in coal prices. Nevertheless we gain

[1] K2K was used to compute the BDS test statistic for the specified range (Kočenda and Briatka 2005). Available from: http://home.cerge-ei.cz/kocenda/software.htm.

the key insight that coal prices exhibit predictable patterns. The results from the BDS and the ARCH test point to the fact that nonlinearities exist in coal prices. The constant variance assumption of coal prices in soundly rejected in Table 3. Since the coal market is a dynamic industry, we expect changes in technology and economic conditions to cause the variance of coal prices to change over time. We therefore model the remaining structure in coal prices by fitting GARCH models to uncover the dynamics of the second moments.

## 4. Coal Price Variability

The estimates of the volatility models are reported in Table 4. The estimates are done by assuming student *t*-distributions for the normalised residuals to allow for fatter tails. Estimates of the parameters are obtained by maximising the likelihood function over sample period.

The estimates in Table 4 indicate that the lagged coal prices for Aggregate, Spot and Contract are significant and predictable for all models GARCH models. Only the estimated GARCH model for Contract shows predictable of the mean up to 3 lags. For Aggregate, all fitted models indicate that the mean is quite predictable up to 2 lags.

A close look at Table 4 reveals that not only is the mean of coal prices predictable, but also that there is a high degree of persistence in the conditional variance. The variance estimates shows significant ARCH and GARCH effects with $\alpha+\beta$ close to unity. In fact, a closer examination of GARCH indicates $\alpha+\beta$=0.94, $\alpha+\beta$=0.88

and $\alpha+\beta$ =0.95 for Contract, Spot and Aggregate respectively. The TGARCH for both Contract and Spot gives $\alpha+\beta$ =0.99 and $\alpha+\beta$ =0.96 respectively. The highly statistically significant estimates of these parameters coupled with their closeness to unity, implies that shocks to the conditional variance of Contract and Spot will be highly protracted. As expected, the parameters of Spot are smaller than Contract, as the transactions are less likely to be linked over time in the Spot market. However, for all EGARCH and the Aggregate TGARCH models, $\alpha+\beta>1$. In this instance the second and fourth unconditional moments do not exist, but the conditional distribution is still well defined. In contrast to the stationary variance case, the impacts of variance shocks remain forever. We could argue that the asymmetric models are either not suited to modelling the coal price series, or simply, the series could well be approximately by alternative GARCH models such as the integrated GARCH. Although an integrated GARCH (IGARCH) process in time series is not unusual, a model of conditional volatility that is non-stationary could be of limited use to coal market participants. A probable parameterization of the volatility process that takes this into account is the Fractionally Integrated GARCH (FIGARCH) model of Bailie *et al* (1996).

Further, from Table 4, the $\beta$ coefficient in the conditional variance equation is considerably larger than $\alpha$ in the vast majority of cases. A large sum of these coefficients implies that a large positive or negative real coal prices causes future forecasts of the variance to be high; this is useful in considering these models for forecasting. Overall, the results show that there is pervasive presence of significant autoregressive conditional heteroscedasticity in coal prices.

Next, we examine whether there is asymmetry in coal prices. Does a negative shock to coal prices (i.e. decrease in this period coal prices) tend to cause variability to rise by more than an increase (positive shock) of the same magnitude? A question of this nature would have implications for coal production and pricing. The $\gamma$ parameter captures this in the EGARCH and TGARCH models, hence for an asymmetric effect $\gamma > 0$ and statistically significant. From Table 4, $\gamma$ is statistically insignificant for Contract and Spot for TGARCH. However, EGARCH captures the asymmetry in coal prices quite well as seen from Table 4, with $\gamma$ being statistically significant and positive across models and disaggregated coal price series. This implies that negative shocks (price falls) persist longer than positive shocks in the coal market. It is suggested that the ability of mines to stop production relative to start new production is a factor in this result.

## 5. Conclusion

A number of models have been used to test the properties of coal price evolution. Coal prices tend to have non-linear properties and a non-constant variance over time. This is not surprising given discovery of new reserves, technological advances in mining, and changes in regulatory policy. The Contract series requires more lags in the AR and GARCH models than the Spot or Aggregate series, likely a result of the price adjustment mechanisms used in contracts and the high transactions cost that come with renegotiation. For all series the persistence of shocks is high, with most GARCH models predicting an $\alpha + \beta$ close to unity, and none below 0.88. The lowest $\alpha + \beta$ comes from the Spot series, which is expected since these are much shorter agreements, which lowers the transactions cost of altering the price. Coal contracts often have price adjustment mechanisms tied to economy-wide indicators like the Consumer Price Index which would explain the high persistence of coal prices. Finally, the series tend to have asymmetric effects with respect to price shocks. It is suggested that this is due to the ability of mines to start new production relative to stopping production.

The wide spread use of coal in the US economy makes an understanding of the evolution of coal prices important for energy and economy-wide modellers. The results here are instructive in the persistence of coal prices and their shocks as well as the differences between prices from long-term contracts and those from the spot market.

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**Figure 1: Coal Prices**

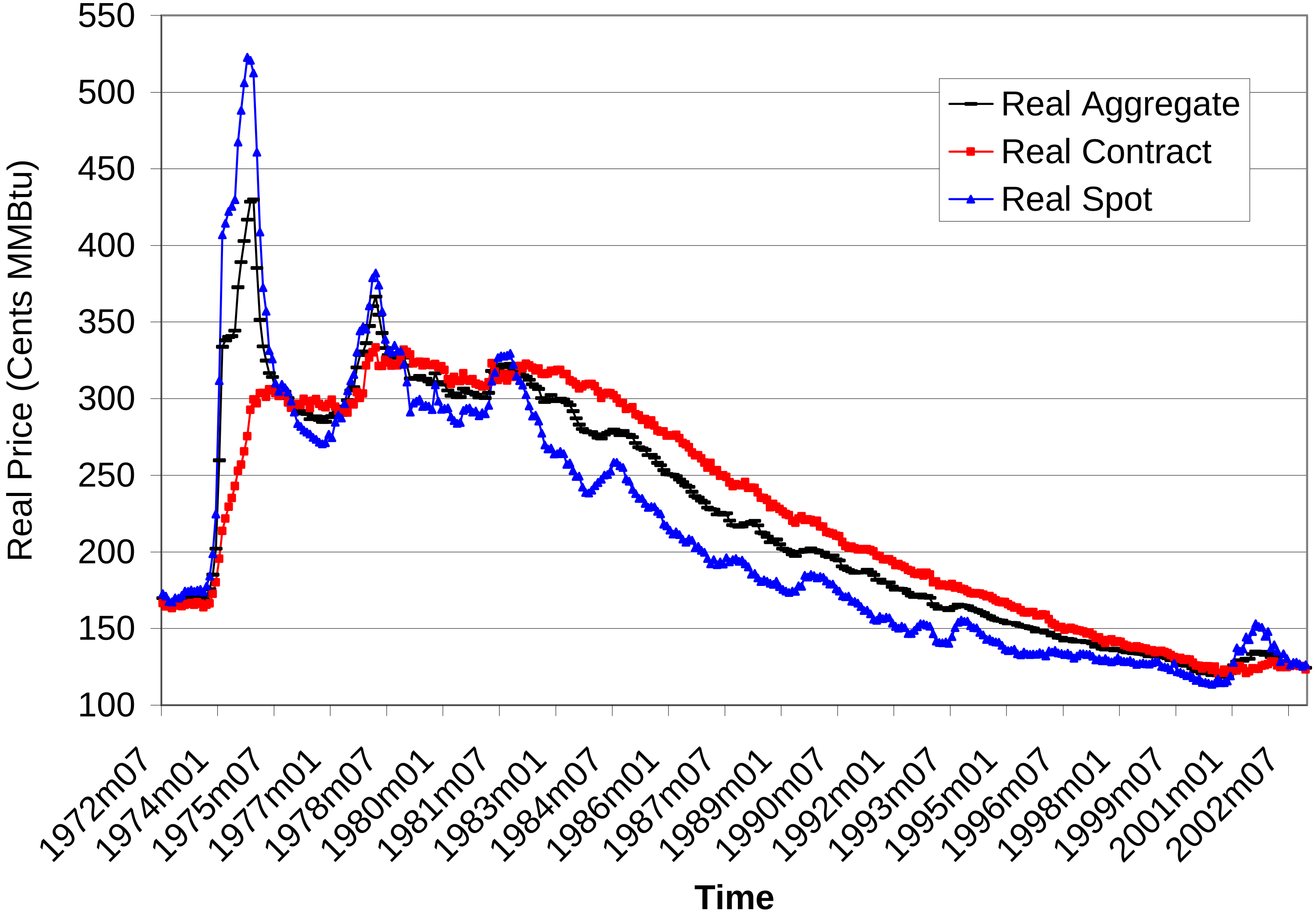

**Table 4: Results of Fitting GARCH models**

| | Contract | | | Spot | | | Aggregate | | |
|---|---|---|---|---|---|---|---|---|---|
| | **GARCH** | **EGARCH** | **TGARCH** | **GARCH** | **EGARCH** | **TGARCH** | **GARCH** | **EGARCH** | **TGARCH** |
| $u$ | -0.003 | -0.003 | -0.003 | -0.004 | -0.004 | -0.003 | -0.0037 | -0.0034 | -0.0032 |
| | (-3.64) | (-6.92) | (-6.83) | (-5.43) | (-5.28) | (-2.72) | (-7.318) | (-6.54) | (-5.659) |
| $\phi_1$ | | | | | 0.216*** | 0.2113*** | 0.161** | 0.178*** | 0.172** |
| | | | | | (3.657) | (3.44) | (2.717) | (3.202) | (2.874) |
| $\phi_2$ | | | | | 0.137*** | 0.133** | | | |
| | | | | | (2.369) | (2.224) | | | |
| $\phi_3$ | 0.193*** | | | | | | | | |
| | (3.66) | | | | | | | | |
| $\alpha_0$ | 0.0001 | -1.489 | 0.0000 | 0.0000 | -1.06 | 0.0000 | 0.0000 | -0.976 | 0.0000 |
| | (2.33) | (-2.77) | (2.23) | (3.09) | (4.123) | (2.956) | (-2.52) | (-4.74) | (3.877) |
| $\alpha_1$ | 0.294*** | 0.523* | 0.381*** | 0.457*** | 0.422*** | 0.448*** | 0.365*** | 0.342*** | 0.446*** |
| | (3.65) | (1.82) | (3.39) | (3.39) | (4.37) | (3.42) | (3.804) | (4.046) | (5.433) |
| $\beta_1$ | 0.625*** | 0.876*** | 0.606*** | 0.426*** | 0.904*** | 0.528*** | 0.588*** | 0.921*** | 0.666*** |
| | (7.45) | (15.37) | (6.58) | (5.73) | (30.82) | (7.025) | (8.32) | (44.59) | (15.19) |
| $\gamma_1$ | | 0.433*** | -0.234 | | 0.145** | -0.229 | | 0.180*** | 0.406*** |
| | | (3.904) | (-1.44) | | (2.83) | (-1.57) | | (3.304) | (4.477) |
| **AIC** | -6.369 | -6.340 | -6.342 | -5.152 | -5.135 | -5.201 | -6.264 | -6.283 | -6.263 |
| **SBC** | -6.304 | -6.276 | -6.278 | -5.099 | -5.071 | -5.115 | -6.200 | -6.208 | -6.188 |
| **ARCH(10)** | 0.938 | 1.124 | 1.307 | 0.774 | 1.458 | 1.1334 | 0.949 | 1.348 | 1.0.98 |
| | [0.497] | [0.343] | [0.224] | [0.653] | [0.153] | [0.336] | [0.487] | [0.203] | [0.362] |
| **LBQ(6)** | 6.1304 | 4.85 | 5.557 | 4.1702 | 11.98 | 7.243 | 5.538 | 11.114 | 5.635 |
| | [0.294] | [0.56] | [0.475] | [0.654] | 0.101] | [0.124] | [0.354] | [0.134] | [0.345] |
| **LBQ(12)** | 12.77 | 13.07 | 14.97 | 7.20 | 12.95 | 11.924 | 17.186 | 11.99 | 13.844 |
| | [0.308] | [0.364] | [0.243] | [0.783] | [0.113] | [0.218] | [0.102] | [0.364] | [0.242] |
| **T.Dist** | 8.634** | 11.42* | 9.964** | 4.074*** | 4.29*** | 5.159*** | 4.591*** | 5.745*** | 19.56 |
| | (2.84) | (1.85) | (2.145) | (3.79) | (3.01) | (3.146) | (3.67) | (2.93) | (1.38) |
| **LL** | 1158.7 | 1163.2 | 1163.3 | 945.31 | 949.12 | 951.99 | 1146.2 | 1150.6 | 1146.9 |

***, **, * indicates significance at 1%, 5% and 10% levels respectively. AIC, SBC represent the Akaike and Schwarz criterion. LBQ is the Ljung-Box statistic. Test statistics are reported in ( ) while *p*-values are reported in [ ]. T-dist is the parameter of the student t-distribution and LL is the log likelihood value of the estimated GARCH models.