Using High, Low, Open and Closing Prices to Estimate the Effects of Cash Settlement on Futures Prices

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Abstract

Prior to 1986, any opening position on feeder cattle futures contract must be settled with physical delivery after the last trading day. Due to dwindling commercial interests, Chicago Mercantile Exchange (CME) subsequently replaced the system with the cash settlement method. It was argued that cash settlement would help reduces the futures price's volatility. In this paper, we adopted stochastic volatility models to investigate this conjecture. The models allow for time varying volatility. Using 4 estimators based on mixtures of high, low, open and close prices, we found all estimators conclude that the volatility of the feeder cattle futures price decreased after switching from physical delivery to cash settlement. The change in the contract specification therefore enhances price discovery and risk management functions of the futures market. Concerning the higher moments of the volatility, different conclusions were derived. Range data, the Parkinson and the Rogers-Satchell estimators all indicate that cash settlement led to a reduction in the volatility of volatility.

Key words: Stochastic Volatility Model, Quasi-Maximum Likelihood, Cash Settlement, Feeder Cattle Futures Contract.

JEL classifications: G1, Q1, C1

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Introduction

Futures market provides two main functions: risk management and price discovery. For the former purpose, an individual with a non-tradable spot position would undertake an opposite position in the futures market expecting the payoffs from the two positions to offset each other (to a great extent). Consequently, an effective futures market must enhance the convergence between spot and futures prices. On the other hand, the futures price also provides useful information for the spot price in the future. For this purpose, a more stable futures price series is deemed more desirable. As the success of a futures contract hinges on these two functions, under constantly changing market conditions commodity exchanges strive to adjust contract specifications to promote trading interests.

Commodity futures contract commonly adopts a physical delivery settlement system. That is, a trader with an open position at the expiration day must make or take the delivery. While this process may require high costs of transporting and storing, it was historically justified as an impediment to excessive speculation in futures markets. Concerns of market manipulations such as corners and squeezes, however, induce the exchanges to allow for multiple deliverable grades and locations (normally at the discretion of the seller). Consequently, the futures price will converge to the cheapest deliverable grade. This results in an additional uncertainty, which discourages the uses of the futures market by traders. Also, as market conditions change, the list of delivery grades and locations (with fixed premia and discounts) may become outdated.

To avoid delivery cost, to reduce manipulation incidences, and to promote the convergence between spot and futures prices, the exchange may adopt a cash settlement system. Hereby, the exchange constructs a cash settlement index. At the maturity date, a cash transfer (calculated from the index) between the trader and the exchange closes an open position. The construction of a reasonable index is therefore the prerequisite for an effective cash settlement mechanism. A narrow-based index consisting of a small number of grades and locations is subject to manipulation whereas a broad-based index reduces the hedging effectiveness. An optimal index (in terms of liquidity or trading volume) should reflect the market conditions. Heterogeneity and non-storability of certain agricultural commodities create difficulties in constructing an appropriate cash index. As a result, commodity futures continue to rely upon physical delivery settlement with few exceptions one of which is the feeder cattle contract.

On the September of 1986 the Chicago Mercantile Exchange (CME) abandoned the physical delivery specification of the feeder cattle futures contract and adopted a cash settlement instead.[1] The CME suggested that the new contracts would have lower basis variability and would attract more commercial interests. Several previous studies, including Elam (1988), Schroeder and Mintert (1988), Kenyon and Bainbridge (1991), and Rich and Leuthold (1992), have found support for the suggestion. However, these studies all assume stationary variances before and after the cash settlement was adopted. Lien and Tse (2000) tested and rejected this assumption. Allowing for time-varying second moments, they adopted a bivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model for the joint generation process of spot and futures prices. They found that cash settlement in the feeder cattle contract both reduced futures market volatility and enhanced the hedging effectiveness. Chan and Lien (2000) applied stochastic volatility models (which also accommodate time-varying second moments) to the same data set and reaffirmed the Lien-Tse results.

Common to all previous studies is the employment of daily or weekly closing price (or settlement price) data. This paper considers the volatility measures that incorporate high, low, opening and closing prices[2]. It is expected that the resulting volatility measures will be more efficient than that constructed from closing prices only. Unfortunately, these data are only available from the futures market. Our analysis is therefore restricted to the effects of cash settlement on futures prices. Specifically, we consider three volatility measures (constructed under the assumption of a Geometric Brownian motion) proposed separately by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991). We then proceed our analysis with the stochastic volatility assumption. Details of each volatility measure and the statistical model are described in the next section.

Volatility Measures and Modeling

Consider a trading day t. Let O_t, C_t, H_t, and L_t denote, respectively, the opening, closing, high and low (futures) prices at day t. The simplest measure related to the volatility is the range, defined as the difference between the high and low prices (in logarithms):

$$R_t = \ln(H_t) - \ln(L_t)\,. \tag{1}$$

Gallant, Hsu, and Tauchen (1999) and Alizadeh, Brandt and Diebold (1999) both found range to be an informative proxy for the volatility.

Assuming an underlying Geometric Brownian motion with no drift for the (futures) price, the joint density function of H_t and L_t can be derived. Based upon the density function Parkinson (1980) proposed a volatility measure as follows:

$$V_{P,t} = 0.361 R_t^2 = 0.361[\ln(H_t) - \ln(L_t)]^2. \qquad (2)$$

It was demonstrated that $V_{P,t}$ could be as much as 8.5 times more efficient than log-squared returns as a volatility-proxy. To incorporate the opening and closing prices, Garman and Klass (1980) suggested the following measure:

$$V_{GK,t} = \frac{1}{2}[\ln(H_t) - \ln(L_t)]^2 - [2\ln 2 - 1][\ln(C_t) - \ln(O_t)]^2. \qquad (3)$$

Both measures are unbiased when the sample data are continuously observed with $V_{GK,t}$ being more efficient than $V_{P,t}$. In reality, the sample data are discretely observed and henceforth both measures incur downward biases. The size of the bias depends upon the observation frequency. Correction methods are available but they require certain parameters that are not empirically available (Yang and Zhang, 2000).

For most financial data, it is likely that the drift term is not zero. In this case, neither Parkinson nor Garman-Klass estimator is the most efficient estimator; see Yang and Zhang (2000) for simulation results. Rogers and Satchell (1991, 1994) proposed an alternative measure that is drift independent:

$$V_{RS,t} = [\ln(H_t) - \ln(O_t)][\ln(H_t) - \ln(C_t)] + [\ln(L_t) - \ln(O_t)][\ln(L_t) - \ln(C_t)]. \qquad (4)$$

When applied to the actual data, this measure is also subject to downward bias problem. A correction method is discussed in Yang and Zhang (2000) but again remains non-practical.

Note that all the above measures are one-period measures. Suppose we have data from N trading days ($t = 1,\ldots, N$). If the volatility remains constant over the N trading days, the multi-period measure would be:

$$\overline{V}_j = (1/N)\sum_{t=1}^{N} V_{j,t}, \tag{5}$$

$j = P$, GK, or RS. A more efficient multi-period measure was provided in Yang and Zhang (2000). When the volatility is non-stationary, a different method is required. In the current literature, there are two popular specifications: GARCH model and stochastic volatility model. In this paper we adopt the latter framework.[3]

Specifically, we assume[4]

$$\log(V_{j,t}) = H_t + e_{j,t}, \tag{6}$$

where $e_{j,t}$ is the zero-mean irregular component and H_t is the systematic component (i.e., the true volatility in logarithm). It is further assumed that H_t follows an AR(1) process:

$$H_t = g + fH_{t-1} + h_t, \tag{7}$$

with h_t being a normal random variable with zero mean and variance s_h^2. Also, h_t is assumed to be uncorrelated with $e_{j,t}$. Alternatively, let $m = g/(1 - f)$ and let $h_t = H_t - m$. Then equation (6) and (7) can be rewritten as follows:

$$\log(V_{j,t}) = m + h_t + e_{j,t}, \tag{6'}$$

$$h_t = fh_{t-1} + h_t. \tag{7'}$$

Note that m is the mean of the true volatility whereas $s_h^2/(1 - f^2)$ is the volatility of the true volatility.

Data Descriptions

Feeder cattle futures price data were obtained from Future Industry Institute Data Center. The data covers the period from November 1981 to April 1991. We constructed a daily series of nearby futures prices, that is, the price of the futures contract whose maturity is the closest for a given day. To avoid the maturity effects, we rolled over the contract month when the trading volume of the next nearby futures contract began to pick up. Normally the rollover occurred around two weeks before the contract expiration day. Excluding Holidays, there are in total 2667 observations. The contract switched from physical delivery to cash settlement in August 1986. In sum, there are 1218 pre-cash settlement and 1449 post-cash settlement observations.

Figures 1 - 4 display range and the three volatility estimates. In each graph, there is a visible change occurring at the switching point signaling a reduction in volatility after the cash settlement was adopted. Summary statistics are presented in Table 1. The mean of the range decreased from 0.0056 to 0.0039 whereas the means of the Parkinson, Garman-Klass, and Rogers-Satchell volatility estimates decreased from 0.0074, 0.0069, and 0.0068 to 0.0038, 0.0037, and 0.0037 respectively. The standard deviation of each volatility proxy also decreased after cash settlement was in place; at the same time, the estimates became more positively skewed and had fatter tails. With the exception of the range, a normal distribution assumption is rejected for each volatility estimate using Bera-Jarque statistics.

Empirical Results

Harvey, Ruiz and Shephard (1994) applied quasi-maximum likelihood (QML) method to estimate equations (6’) and (7’). They suggested $e_{j,t}$ be treated as a normal random variable. Consequently, Kalman filter can be applied to generate the quasi-maximum likelihood estimator. Various alternative estimation methods had been proposed, including the Generalized Method of Moment (GMM) type estimator proposed by Andersen (1994) and Markov Chain Monte Carlo (MCMC) simulation estimator suggested in Jacquier, Polson and Rossi (1994) and Kim, Shephard and Chib (1998). In this paper, we adopted the quasi-maximum likelihood estimator for its simplicity. Moreover, Ruiz (1994) found that, for financial time series data QML estimator has good finite-sample properties. Alizadeh, Brandt and Diebold (1999) also showed that QML is highly efficient for range-based method.

We begin with the stochastic volatility model of range. Similar to Alizadeh, Brandt and Diebold (1999), we found the range data conform to a normal distribution. Therefore, QML estimate is an efficient estimate. The estimation results are as follows:

Physical Delivery Period

$$\log(R_t) = \underset{(0.093)}{-12.879} + h_t + e_{R,t}\,,$$

$$h_t = 0.927 h_{t-1} + \boldsymbol{h}_t\,,$$

$$\hat{s}^2_{R,t} = 2.500, \hat{s}^2_{h,t} = 0.043\,.$$

Cash Settlement Period

$$\log(R_t) = \underset{(0.067)}{-13.596} + h_t + e_{R,t}\,,$$

$$h_t = 0.922 h_{t-1} + \boldsymbol{h}_t\,,$$

$$\hat{\sigma}^2_{R,t} = 2.738, \hat{\sigma}^2_{\eta,t} = 0.024 .$$

The numbers within the parentheses are the corresponding root mean squared errors. Both results indicate that range contains mostly noise (instead of volatility information). Upon taking anti-log, the estimated mean volatility for range decreased from 2.551×10^{-6} to 1.245×10^{-6} after cash settlement was adopted. The persistence of the volatility movement remained unchanged (i.e., the persistence parameters are 0.927 and 0.922 respectively). The volatility of volatility is calculated to be 0.306 for the physical delivery period and 0.160 for the cash settlement period. Thus, using range as a proxy, we found the volatility of the feeder cattle futures price became more stable with a smaller mean, which enhances the price discovery and risk management functions of the futures market.

Applying the Parkinson volatility estimates, we have the following stochastic volatility model:

Physical Delivery Period

$$\log(V_{P,t}) = \underset{(0.074)}{-11.090} + h_t + \varepsilon_{P,t} ,$$

$$h_t = 0.902 h_{t-1} + \eta_t ,$$

$$\hat{\sigma}^2_{R,t} = 2.270, \hat{\sigma}^2_{h,t} = 0.043 .$$

Cash Settlement Period

$$\log(V_{P,t}) = \underset{(0.040)}{-12.383} + h_t + \varepsilon_{P,t} ,$$

$$h_t = 0.852 h_{t-1} + \eta_t ,$$

$$\hat{\sigma}^2_{R,t} = 2.360, \hat{\sigma}^2_{h,t} = 0.028 .$$

Upon taking anti-log, we found the mean volatility decreased after cash settlement was adopted (i.e., from 15.264 $\times$ 10^{-6} to 4.190 $\times$ 10^{-6}). Also, the volatility of volatility declined from 0.231 to 0.102. The results are consistent with those derived from the range data. However, in this case the volatility became less persistent after cash settlement was effective.

We now turn to the Rogers-Satchell volatility estimator, which is robust to a possible drift in the underlying stochastic process. The estimation results are presented in the following.

<u>Physical Delivery Period</u>

$$\log(V_{RS,t}) = \underset{(0.081)}{-11.240} + h_t + \varepsilon_{RS,t} ,$$

$$h_t = 0.912 h_{t-1} + \eta_t ,$$

$$\hat{\sigma}^2_{R,t} = 2.281, \hat{\sigma}^2_{h,t} = 0.021 .$$

<u>Cash Settlement Period</u>

$$\log(V_{RS,t}) = \underset{(0.079)}{-12.470} + h_t + \varepsilon_{RS,t} ,$$

$$h_t = 0.965 h_{t-1} + \eta_t ,$$

$$\hat{\sigma}^2_{R,t} = 2.384, \hat{\sigma}^2_{h,t} = 0.008 .$$

In contrast to the Parkinson estimator, herein the volatility became more persistent in the cash settlement period. Both the mean volatility and the volatility of volatility decreased (from 13.14×10^{-6} to 3.84×10^{-6} and from 0.125 to 0.116, respectively).

Finally, we turn to the Garman and Klass volatility estimator. The results are as follows:

Physical Delivery Period

$$\log(V_{GK,t}) = \underset{(0.092)}{-11.378} + h_t + \varepsilon_{GK,t},$$

$$h_t = 0.922 h_{t-1} + \eta_t,$$

$$\hat{\sigma}^2_{R,t} = 2.303, \hat{\sigma}^2_{h,t} = 0.049 .$$

Cash Settlement Period

$$\log(V_{GK,t}) = \underset{(0.042)}{-12.592} + h_t + \varepsilon_{GK,t},$$

$$h_t = 0.008 h_{t-1} + \eta_t,$$

$$\hat{\sigma}^2_{R,t} = 0.030, \hat{\sigma}^2_{h,t} = 2.484 .$$

Again, we found the mean volatility decreased from the first period (11.444×10^{-6}) to the second period (3.399×10^{-6}). However, using the Garman-Klass estimator we found there was no volatility persistence in the cash settlement period. Also, in the cash settlement period the Garman-Klass volatility estimator contains little noise (in sharp contrast to all other estimators). The resulting consequence is that, the volatility of volatility increased from 0.327 to 2.484 after cash settlement was in effect.

Conclusions

In this paper, we applied four volatility estimators of the feeder cattle futures price to examine the effects of cash settlement. Using a stochastic volatility model specification, we found all estimators conclude that the volatility of the feeder cattle futures price decreased after switching from physical delivery to cash settlement. The change in the contract specification therefore enhances price discovery and risk management functions of the futures market. Concerning the higher moments of the volatility, different conclusions were derived. Range data, the Parkinson and the Rogers-Satchell estimators all indicate that cash settlement led to a reduction in the volatility of volatility. The Garman-Klass estimator suggested otherwise. Note that quasi-maximum likelihood estimator is efficient for the range data whereas the Rogers-Satchell volatility estimator is drift independent. The results derived from these two estimators are deemed more reliable. We therefore conclude that cash settlement reduces both the mean and the volatility of the volatility in feeder cattle futures prices.

Footnotes

1. Beginning with the February 1997 contract, the CME replaced the live hog futures contract with the lean hog futures contract. The latter is cash settled and adopts a carcass-based pricing system in accordance with industry practice (Ditsch and Leuthold, 1996). Because the two major changes were implemented simultaneously, the analysis on the effects of cash settlement is somewhat contaminated.

2. When options prices are available, the implied volatility (IV) calculated from these prices constructs an alternative estimate. However, the existence of "volatility smile" cast doubt on the reliability of the IV estimates. Canina and Figlewski (1993) also argued that IV is not a good estimator for actual volatility.

3. The choice between GARCH and stochastic volatility (SV) models is not an easy one. Andersen (1994, 1996) compared the performance of both models using IBM stock returns and found that neither dominates the other. Heynen and Kat (1994) suggested that GARCH models outperform SV models in modeling exchange rates but the opposite is true for stock index returns. Kim, Shephard and Chib (1998) found SV models are superior to simple GARCH but inferior to Student t-GARCH models. Hwang and Satchell (2000) argued that GARCH models are more suitable for describing some stylized facts of volatility while SV models were developed to capture the arrival of information, a point echoed by Andersen (1996). Moreover, the proliferation of parameters in multivariate GARCH models and the positive semi-definiteness restrictions required for the variance-covariance matrix render the approach less attractive.

4. Conventional approach adopts the log-squared or the log-absolute return as a volatility proxy and applies a stochastic volatility specification to the logarithm of the volatility

(see Harvey, Ruiz and Shephard, 1994). To be consistent, we also model $\log(V_{j,t})$ instead of $V_{j,t}$.

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Table 1: Summary Statistics of Volatility Measures

Physical Delivery Period (sample size =1218)

Summary Statistics	R	V_P	V_{GK}	V_{RS}
Mean	0.0056	0.0074	0.0069	0.0068
Std. Dev.	0.0027	0.0075	0.0071	0.0079
Skewness	1.0069	2.5065	3.6889	3.9540
Exc. Kurtosis	1.2283	9.7007	25.911	27.889

Cash Settlement Period (sample size = 1449)

Summary Statistics	R	V_P	V_{GK}	V_{RS}
Mean	0.0039	0.0038	0.0037	0.0037
Std. Dev.	0.0020	0.0044	0.0043	0.0048
Skewness	1.4647	3.8938	5.6268	5.8650
Exc. Kurtosis	3.4254	27.402	64.762	63.996

Figure 1. Daily range of feeder cattle futures price

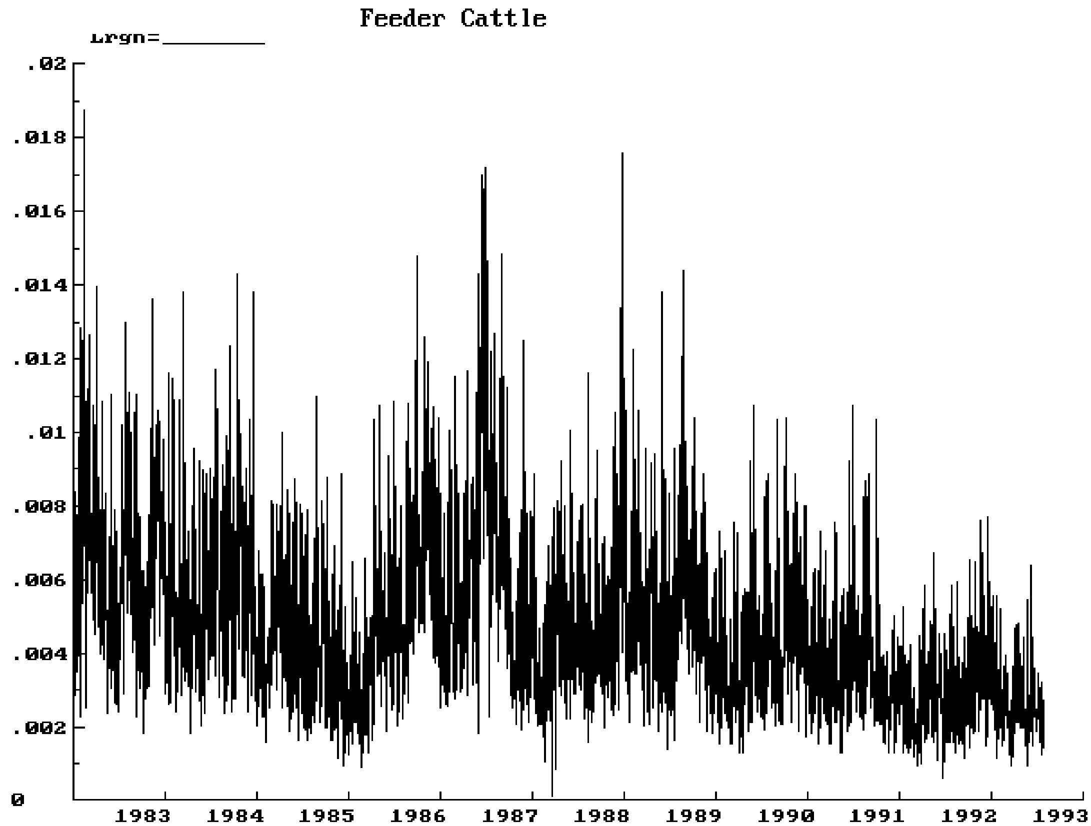

Figure 2. Parkinson volatility estimates of feeder cattle futures price

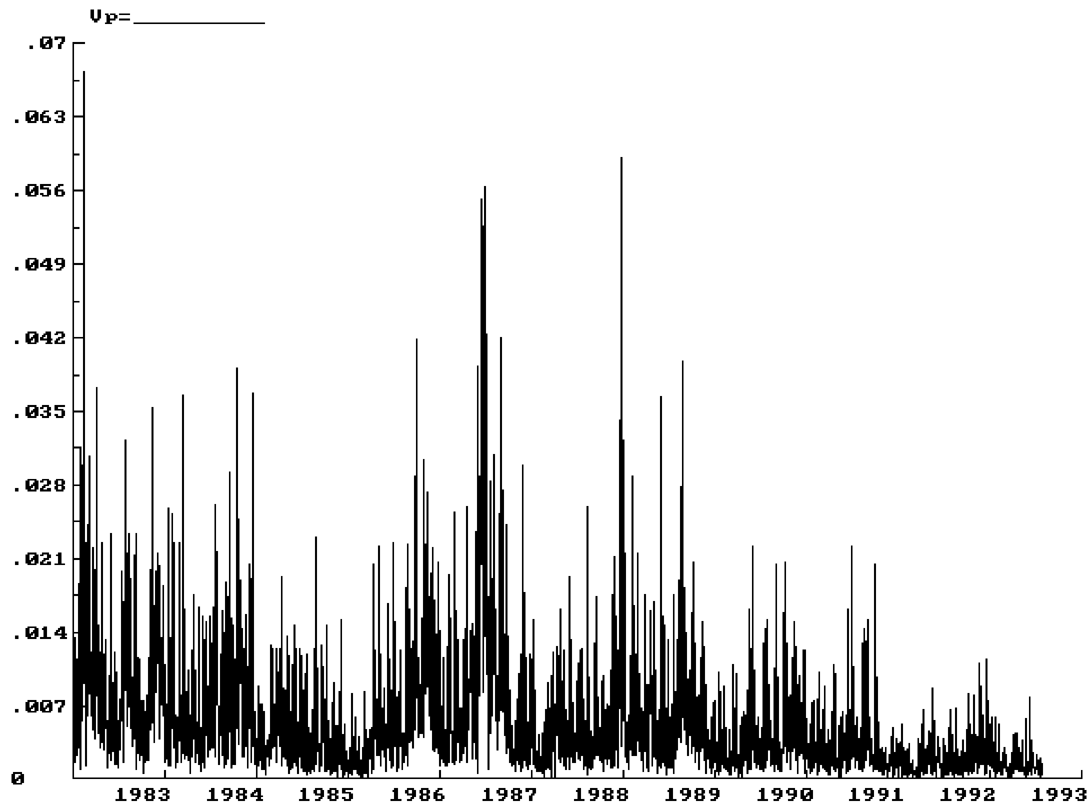

Figure 3. Rogers-Satchell volatility estimates of feeder cattle futures price

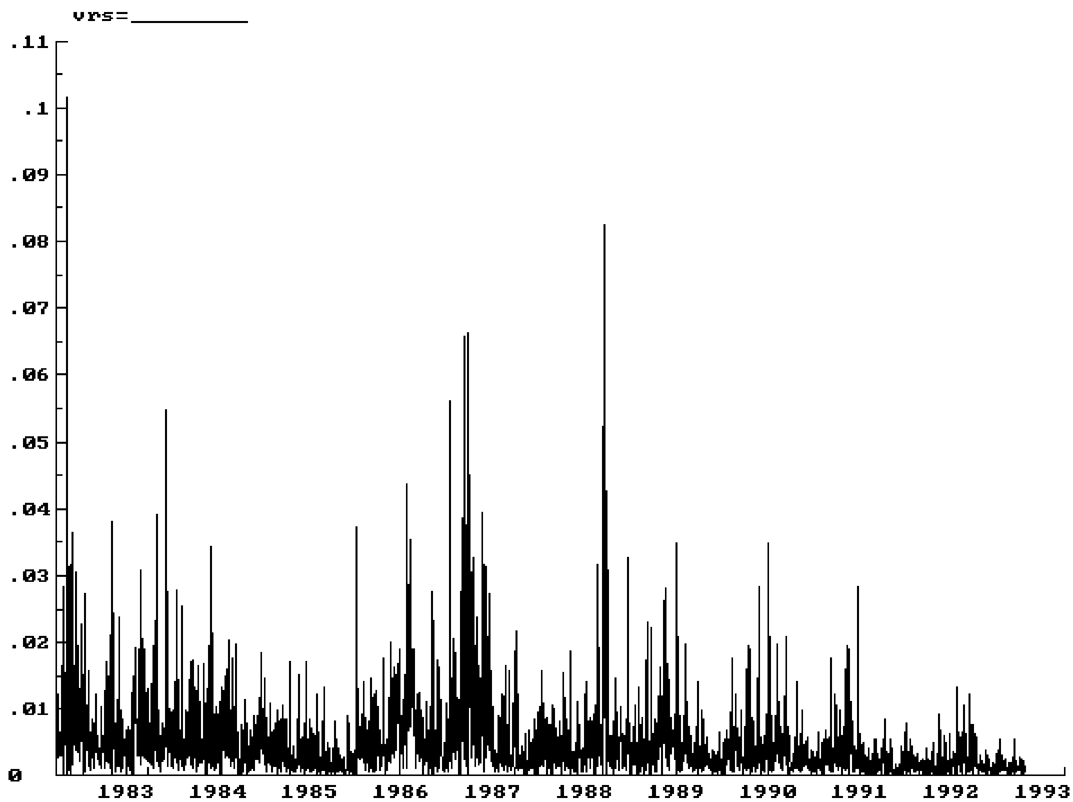

Figure 4. Garman-Klass volatility estimates of feeder cattle futures price