THE FUTURES MARKET EFFICIENCY OF GOLD, SILVER AND COPPER

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ABSTRACT

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Gold, silver, and copper futures market efficiency is examined by looking at whether futures contract prices contain useful information about future spot prices.

The Fama and French (1987) regression approach is applied to test whether the futures price has forecast power on the spot price or if it contains information about the premium to be realized at maturity. The result suggests that the futures price of gold has some forecast power while the futures price of copper contains information about the time-varying premium.

Unit root and co-integration analysis indicates that futures prices and spot prices of gold, silver, and copper are co-integrated at 95% confidence level. This means that the futures contract prices are unbiased predictors of future spot prices. Thus, the efficiency of the gold, silver, and copper futures markets is supported.

The univariate GARCH test finds evidence of conditional time-varying volatility for both futures and spot series. Also, positive asymmetry where positive price shocks are associated with greater volatility increases than negative price shocks is revealed.

As the gold, silver and copper futures contract series and spot series are almost perfectly correlated, naïve or 1-1 hedging reduces almost all of the variance and realizes high hedging effectiveness. The strong correlation of futures and spot returns supports the hypothesis that futures markets are efficient.

Keywords: futures; market efficiency; GARCH; hedge effectiveness

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1. Introduction

The efficiency of futures markets is a controversial issue in the financial area. It is still debatable that whether futures contract price contains useful information regarding future spot price movement.

There are two popular views of commodity futures prices. The theory of storage of Kaldor(1939), Working (1948), Brennan (1958), and Telser (1958) explains the difference between contemporaneous spot and futures prices in terms of interest forgone in storing a commodity, warehousing costs, and a convenience yield on inventory. Accordingly, in a non-arbitrage efficient market, futures contract investors should focus on current spot prices, interest rates, warehouse costs, and convenience yield instead of the expectation of the spot price fluctuation coupled with the risk related to the spot price. This fundamental view is similar to the intrinsic valuation of stocks used to calculate any discounted cash flows in order to derive the value of stocks. For a manufacturer who is in the underlying commodity industry, storage cost theory is straightforward when making a choice between spot commodity and futures contracts.

The alternative view splits a futures price into an expected risk premium and a forecast of a future spot price. For investors and speculators who have no interest in holding the underlying commodity but are only interested in pursuing capital gains, this view is similar to the Capital Asset Pricing Model focusing on the expected risk premium and future spot price movement to some degree.

Fama and French (1987) examine the above two models of commodity futures prices and find the strong relationship between futures prices and storage-cost variables. They do not find strong evidence that futures prices contain premiums or power to forecast spot prices.

According to Fama and French, the marginal convenience yield arises because inventory can be productive. For example, there may be a convenience yield from holding inventories of some commodities (such as gold) because they are inputs to the production of other commodities (such as jewelry). Or there may be a convenience yield from holding inventories to meet unexpected demand. The theory of storage predicts a negative relation between convenience yields and inventories. Under the theory of storage, inventory seasonals generate seasonals in the marginal convenience yield and in the difference between the futures contract price and the spot price, i.e. the basis. The authors tested for seasonals in the basis. They found that precious metals have the lowest basis standard deviations while animal products have the largest basis standard deviation. Given the lowest storage cost for precious metals, their regression results indicate that the interest rate explains much of the basis variance for precious metals. Evidence of seasonal variation in the basis of seasonally produced agricultural commodities is found. These results are consistent with the theory of storage.

As for forecast power and premiums view, Fama and French ran regressions of the change in the spot price and the premium on the basis. Evidence that the coefficient is positive for change in the spot price means the basis observed at time t contains information about the change in the spot price from t to maturity time T.

Equivalently; the futures price has power to forecast the future spot price. Evidence that the coefficient is positive for premium means the basis observed at t contains information about the premium to be realized at T. Predictable variation in the realized premium is evidence of a time-varying expected premium. Nevertheless, these regressions have their limitations. An irrational forecast of the spot price in the futures price shows up as a time-varying expected premium, while measurement error in the spot price appears as forecast power. Fama and French found that there is a relation between basis variability and evidence that futures prices have time-varying expected premium or power to forecast future spot prices. Commodities with large basis variability, such as eggs, show strong forecast power. Commodities with low basis variation like gold and copper have unreliable results in the test for forecast power and premiums. Fama and French concluded that the low basis variances of the precious metals allow precise estimation of the interest-rates response predicted in theory of storage, but they precluded a reliable split of the basis between the expected premium and the expected spot-price change. At the other extreme, the high basis variances of the animal products preclude reliable estimates of the interest-rate coefficient, but their futures prices have power to forecast future spot prices.

Gibson and Schwartz (1990) used a two-factor pricing model to make the theory of storage more realistic when they forecast the futures price of crude oil. They relaxed the constant convenience yield assumption by allowing for a stochastic convenience yield. They assumed that the spot price of oil has a lognormal-stationary distribution, and the convenience yield follows a mean reverting pattern, as well as the spot price of oil and the net convenience yield follow a joint diffusion process. Using Ito's Lemma, abstracting from interest rate uncertainty, and invoking the standard perfect market assumptions, Gibson and Schwartz derived the price of a futures contract on one barrel of crude oil as the following partial differential equation:

$$1/2F_{SS}S^2\sigma_1{}^2 + 1/2F_{\delta\delta}\sigma_2{}^2 + F_{S\delta}S\rho\sigma_1\sigma_2 + F_S S(r-\delta) + F_\delta(k(a-\delta)-\lambda\sigma_2) - F_r = 0 \quad (1)$$

subject to the initial condition: $F(S,\delta,0) = S$. They used weekly NYMEX crude oil data from 1984 to 1988. The performance of their model is better for short-term futures contract compared to that for long-term futures contract.

Switzer and El-Khoury (2006) investigated the efficiency of the NYMEX crude oil futures contract market during periods of extreme volatility from onset of the 2003 Iraqi war to the formation of the new Iraqi government. They found that crude oil futures contract prices are co-integrated with spot prices and are unbiased predictors of future spot prices. The authors identified the positive asymmetric volatility characteristics of both futures and spot prices. This means that increased volatility is associated with positive price shocks. They concluded that hedging performance can be improved when asymmetries are accounted for.

In this paper, gold, silver and copper futures market efficiency is tested. Gold and silver have become the most popular precious metals traded by investors. Copper is the world's third most widely used metal due to its electrical and mechanical properties. Its considerable commercial importance can be seen from the 1995 collapse of Baring Bank due to its copper futures trades.

2. Data

As the New York Mercantile Exchange (NYMEX) becomes the most popular commodities futures contract market, the NYMEX gold, silver and copper weekly closing prices are used for both the spot prices and futures prices.

The data are obtained from Bloomberg Database and cover the period extends from November 1995 to June 2006. In order to avoid the thin trading problem, only the futures contracts that have less than 3 months to maturity are used.

Figures 1, 2, and 3 show the futures prices and spot prices for gold, silver, and copper from November 1995 to June 2006.

3. Methodology

3.1 Forecast power and premiums

The Fama and French (1987) regression approach is used to test time-varying expected premiums and price forecast power in futures prices. Two regressions of the change in the spot prices and the premium on the basis are employed.

$$S(T) - S(t) = a_1 + b_1[F(t,T) - S(t)] + u(t) \qquad (2)$$

$$F(t,T) - S(T) = a_2 + b_2[F(t,T) - S(t)] + z(t) \qquad (3)$$

where $F(t,T) - S(t)$ is the basis at time t, $S(t)$ is the observed spot price at time t, $F(t,T)$ is the futures contract with maturity time T price at time t, and $u(t,T)$ and $z(t,T)$ are the error terms.

Evidence that b_1 is significantly different from 0 will imply that a futures contract price at time t contains information about the future spot price, or the futures prices have forecast power on the future spot prices. Evidence that b_2 is significantly different from 0 will imply that the basis observed at t has a relation with the premium to be realized at maturity.

The results are reported in Tables 1, 2 and 3.

[Insert Tables 1, 2, and 3 here]

The positive b1 in regression (2) of gold suggests that futures prices at time t contain some information about future spot prices at time T, or the gold futures prices have some forecast power on future gold spot prices.

The positive b2 in regression (3) of silver and copper supports the time-varying risk premium hypothesis. The silver and copper futures prices observed at t contain information about the premium to be realized at T.

In order to check the reliability of the estimations for regressions (2) and (3), the Wald tests are applied for both regressions. The null hypothesis's are a=0 and b=1, a=0, and b=1 respectively. The results are reported in tables 4, 5, and 6.

[Insert Tables 4, 5, and 6 here]

For gold and silver, the constant term is not significantly different from zero. The estimation of b is not significantly reliable, and the Wald test did not give robust support on whether b is equal to 1.

For copper, the constant term is significantly different from zero at 10% significance. The estimation of b1 is different from 1 at 1% significance. The Wald test result indicates that the positive b2 hypothesis can not be rejected. The copper futures contract price contains information about the premium to be realized at maturity.

3.2 Unit root and co-integration test

As mentioned above, the Fama and French (1987) regression approach has its limitations.

Simple use of linear regressions on non-stationary time series data has been showed to be a dangerous approach that could produce spurious correlation. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series are said to be co-integrated.

The use of unit root and co-integration techniques is widespread in time series analysis especially futures prices and spot prices analysis.

The co-integration of futures and spot price series is a necessary condition for market efficiency, since the Efficient Market Hypothesis implies that the futures price is an unbiased predictor of the future spot price. If the two series are co-integrated, S_t and F_{t-1} move together and will not tend to drift apart over time. If this is the case, then the futures price is an unbiased predictor of the future spot price.

First, detrended Dickey-Fuller tests, Augmented Dickey-Fuller tests, and Phillips-Perron tests are used for unit root tests. The results are reported in tables 7, 8, and 9.

[Insert Tables 7, 8, and 9 here]

The results show that all gold, silver and copper futures and spot price series have unit root, e.g. they are characterized by stochastic trends (non-stationary), while their first differences are stationary.

Next, Johansen's (1988) approach is applied to test for co integration. An unrestricted K-variable VAR error correction mechanism was employed:

$$\Delta X_t = A + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \qquad (4)$$

where X_t is a k-vector of non-stationary I(1) variables; Π and Γ are matrices of coefficients ; A is deterministic variables, and ε_t is a vector of error terms.

The co-integration relationship is examined by looking at the rank of the matrix Π of coefficient. If Π =0, there is no co-integration vector, hence no co-integration relationship. If Π=1, then there is one co-integration vector; the two series are co-integrated.

The results are reported in tables 10, 11, and 12.

[Insert Tables 10, 11, and 12 here]

The test statistics reject the assumption of no-co-integration. For gold and silver, the tests suggest a one equation co-integration. For copper, the tests suggest a two equation co-integration. The co-integrating vector results suggest that there is a relationship between spot and futures prices for gold, silver and copper. The futures price contains some information about spot price.

3.3 GARCH test

Commodity futures and spot prices are often characterized by conditional, time-varying volatility with ARCH/GARCH features. The symmetric GARCH model assumes that a negative shock ($\varepsilon_t < 0$) and a positive shock ($\varepsilon_t > 0$) have the same effect on the conditional variance. To allow for asymmetric effects of shocks (i.e. that depend on the sign of the shock) on conditional variance, Glosten et al (1993) (GJR) introduced the asymmetric GARCH variant:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 \varepsilon_{t-1}^2 I_{t-1} \qquad (5)$$

where $I_{t-1} = \begin{cases} 1, \varepsilon_{i,t} \geq 0 \\ 0, \varepsilon_{i,t} < 0 \end{cases}$

The short-run persistence of positive shocks is given by $\alpha_1 + \gamma_1$ and short-run persistence of negative shocks is given by α_1. Estimates of the GARCH (1, 1) model and the GJR-GARCH model for spot and futures prices are reported in Tables 13 and 14 respectively.

[Insert Table 13 and 14 here]

Both models provide a good explanation for futures and spot series. Both futures and spot series exhibit statistically significant conditional heteroscedasticity for all three metals. Table 13 also reveals strong evidence for the presence of persistence in volatility (Integrated GARCH) where the sum of α_1 and β_1 is close to one.

Table 14 displays estimates of the asymmetric GARCH model. Significant positive asymmetry in the futures and spot series is found: positive price shocks are associated with greater volatility increases than negative price shocks. This contrasts with typical results for equity markets, where negative asymmetry is observed – i.e. volatility increases more on price declines due to leverage effects (e.g. Glosten et al (1993)). Gold and silver are the most important precious metal. Although they are no longer the only hard currency in the world, their prices have a large effect on markets. Gold and silver price increases may reflect the increased uncertainty on the macro economy and financial market. The increased uncertainty of macro economy and the financial market may lead to the increased volatility of gold and silver prices when there is a positive price shock. At the same time, gold and silver are rare natural resources and have been widely used in many industries. The increasing demand and limited supply capability will lead to increased price and volatility simultaneously. For copper, as it is a widely-used industrial raw material, its price increases are often associated with supply shortage due to production shocks and /or growing demand. In addition, the 2005 and 2006 volatility shock in copper prices may have partially originated from a Chinese copper futures trader who claimed to be backed by China's huge national copper reserve. This trader's speculative short positions on copper futures incurred tremendous losses and almost went to default. When these short positions were covered, the copper price increased dramatically with abnormal high volatility.

3.4 hedge effectiveness

In order to minimize the negative effect of price shocks, many institutions use futures contracts for hedging. But it is still debatable on how to improve hedge effectiveness.

The return on an unhedged portfolio can be written as:

$$R_u = \frac{S_{t+1} - S_t}{S_t} \qquad (6)$$

While the return on a hedged portfolio is:

$$R_h = \frac{S_{t+1} - S_t}{S_t} - h(\frac{F_{t+1} - F_t}{F_t}) \qquad (7)$$

Where F_t and S_t are the futures and spot prices at time t, and h is the hedge ratio. R_h is the return generated when holding one unit long position of spot and short on h units of futures at time t.

The variance of an unhedged portfolio is:

$$Var(U) = \sigma_s^2 \qquad (8)$$

The variance of a hedged portfolio is:

$$Var(H) = \sigma_s^2 + h^2\sigma_f^2 - 2h\sigma_{s,f} \qquad (9)$$

Where σ_s, σ_f represent the standard deviation of the spot and futures prices, and $\sigma_{s,f}$ represent the covariance of both series.

According to Ederington (1979) and Park and Switzer (1995), hedging effectiveness can be measured by the percentage reduction in variance of the hedge portfolio to the unhedged portfolio:

$$HE = \frac{Var(U) - Var(H)}{Var(U)} \qquad (10)$$

Another way to measure the hedging effectiveness is checking whether the hedged portfolio has a zero return which means the returns on the futures contract exactly offset the returns on the spot price over the hedging period.

The percentage reduction in variance method is applied to check the hedging effectiveness because the initial motivation of hedging is to reduce variance.

The hedging horizon is one week. The Friday closing prices are used for both the spot and futures. For the futures contracts, the price of the nearest contract is used and rolled over to the week prior to expiration. For each metal, the sample consists of 174 observations ranging from March 7th, 2003 to June 30th, 2006.

Four alternative implementations of hedge ratio are checked:

(1) Naïve or 1-1

(2) OLS

(3) Symmetric bivariate GARCH

(4) Asymmetric bivariate GARCH.

For naïve or 1-1 hedging, the hedge ratio is constant 1. The hedged portfolio always hold one unit long position of spot and short on one unit of futures.

For OLS hedging, use a rolling window of 144 observations to ensure sufficient data for the estimation of the parameters. Out of sample hedge ratios are computed for observations 145-174, and hedging effectiveness is measured for a total of 30 observations.

For symmetric bivariate GARCH, the distribution of the residuals is:

$\varepsilon_t \sim N(0, H_t)$,

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}'A \quad (11)$$

where H_t is the 2x2 variance-covariance matrix, A and B are matrices of coefficients, and C is an upper triangular matrix of intercept coefficients. ε_t is the vector of residuals with conditional mean 0 and conditional variance-covariance H_t.

For asymmetric bivariate GARCH, the covariance matrix (11) is replaced by:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + D'\eta_{t-1}\eta_{t-1}'D \quad (12)$$

where D is a matrix of coefficients, and η_t is the additional quadratic form of the vector of negative return shock. H_t is a linear function of its own past values as well as of values of squared shocks.

The time-varying hedge ratios, h_t^*, can be obtained from the variance estimated in models (11) and (12).

$$h_t^* = {h_{sf,t}}/{h_{f,t}} \quad (13)$$

As bivariate GARCH model can capture the conditional time-varying volatility feature of futures and spot prices, it may help to improve the parameter estimation and hence the hedging effectiveness. Same for OLS hedging, use a rolling window of 144 observations, and compute hedge ratios for out of sample, a total of 30 observations.

The window size of 144 samples comes out after many trials. The initial window size was 74 samples. Serious non-convergence problem was encountered when trying to solve the GARCH model. After increasing the window size to 144 samples and adopting the more restricted constant correlation model for GARCH test, the non-convergence problem is resolved.

The out-of-sample hedging effectiveness results are shown in table 15.

[Insert Table 15 here]

All naïve, OLS, and bivariate GARCH hedging realizes significant hedging effectiveness for the three metals. The differences of hedging effectiveness among the four hedging are very small. Most of the variance is reduced to a degree that further improvement is almost impossible. The symmetric bivariate GARCH hedging outperforms other hedgings for all three metals. The average hedge ratios of OLS hedging and bivariate GARCH hedging are close to 1, see table 16. This suggests strong correlation between futures contract and spot price return.

[Insert Table 16 here]

The correlation between futures contract and spot price return is examined. The result is reported in table 17. It shows that for all three metals, the futures contract and spot price return are almost perfectly correlated from March 7th, 2003 to June 30th, 2006.

[Insert Table 17 here]

The strong correlation between futures and spot return explains why the simple naïve or 1-1 hedging for all three metals reduces most of the variance, and supports that the futures contract prices are unbiased predictors of the future spot prices.

4. Conclusion

This paper examines the futures market efficiency for gold, silver, and copper during the period from 1995 to 2006.

The traditional Fama and French (1987) regression approach is used to test time varying expected premiums and price forecast power in futures prices. The results suggest that the gold futures price has some forecast power on future gold spot prices, and that the copper futures contract price contains information about the premium to be realized at maturity.

The more robust unit root and cointegration analysis are employed to test market efficiency. The result indicates that for gold, silver and copper, their futures contract prices are an unbiased predictor of the future spot price.

The univariate GARCH tests reveal the long-term volatility persistence and volatility clustering of futures and spot series for gold, silver and copper. Furthermore, the positive asymmetric GARCH effect is found in futures and spot series for all three metals.

The naïve or 1-1 hedge reduces most of the variance for all three metals. The strong correlation between futures and spot returns supports the idea that 1-1 hedging can realize high hedging effectiveness. This is consistent with that the futures market is efficient.

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Figure 1 – Gold futures contract and Spot price from Dec 1st, 1995 to June 30th, 2006

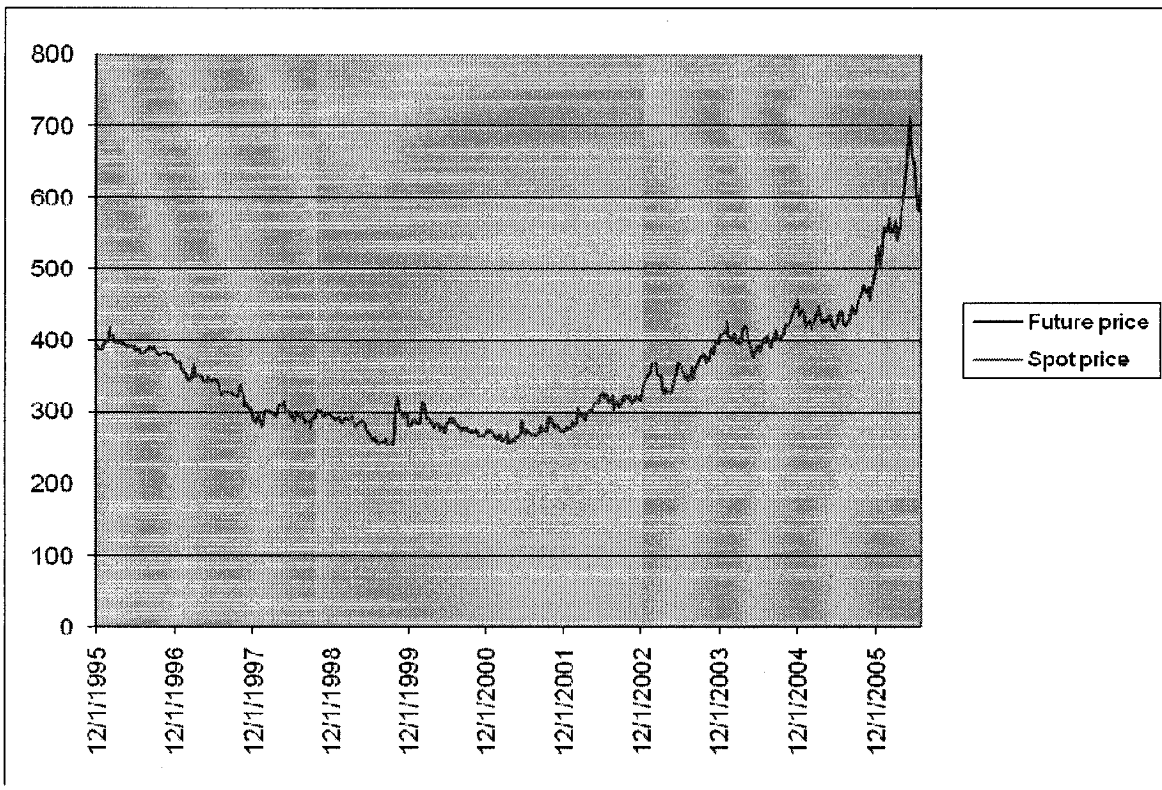

Figure 2 – Gold futures contract and Spot price from Jan 6th, 2006 to June 30th, 2006

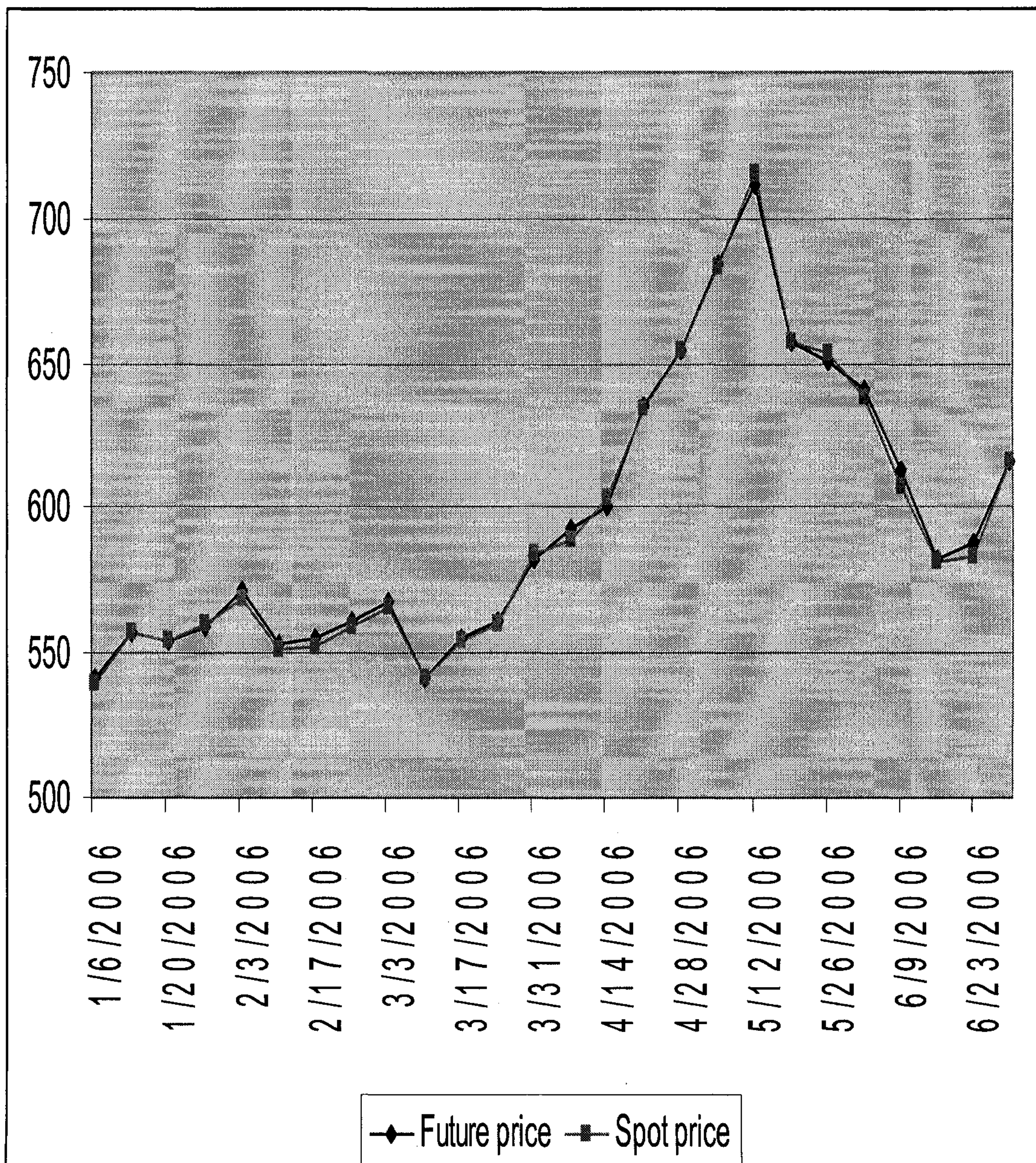

Figure 3 – Silver futures contract and Spot price from Nov 3rd, 1995 to June 30th, 2006

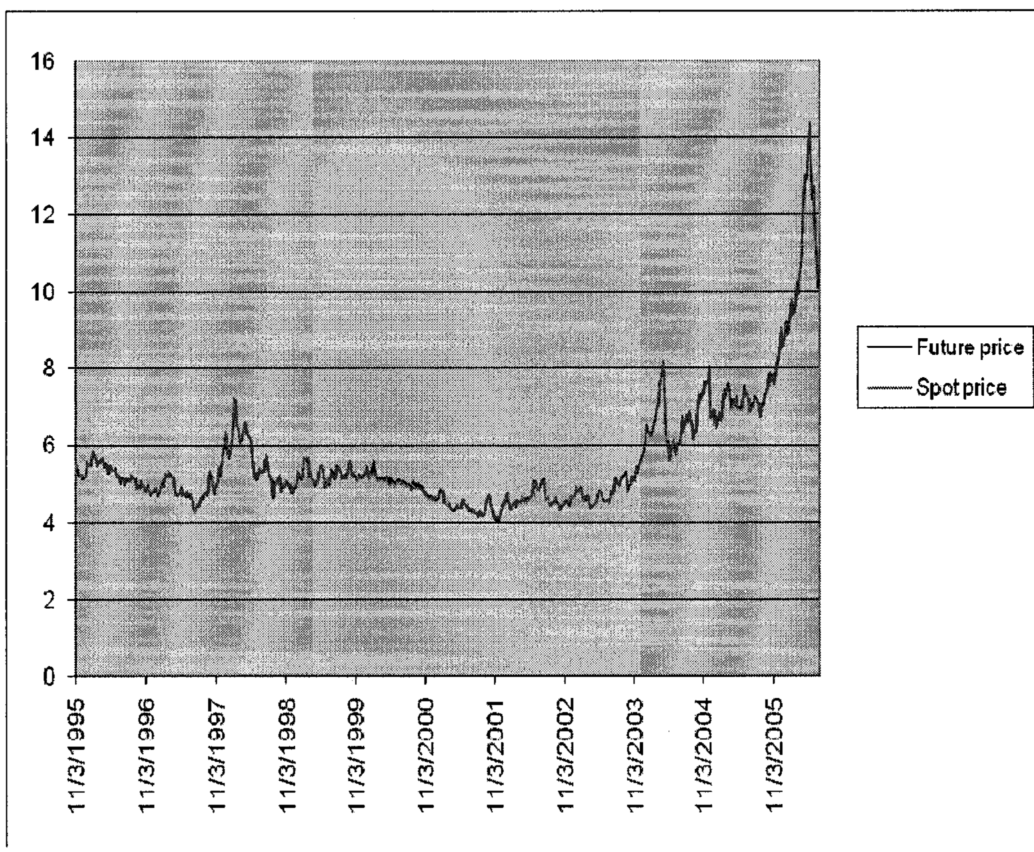

Figure 4 – Silver futures contract and Spot price from Jan 6th, 2006 to June 30th, 2006

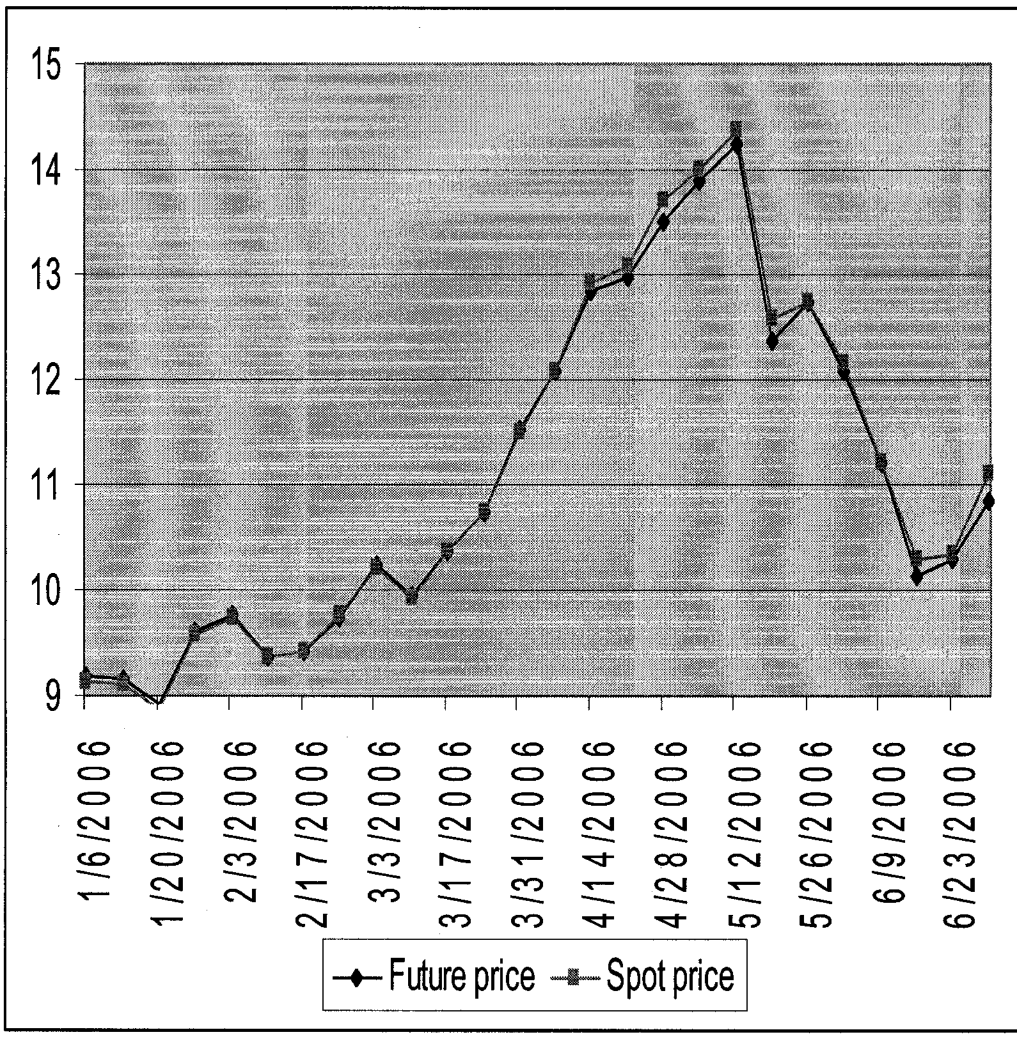

Figure 5 – Copper futures contract and Spot price from Nov 3rd, 1995 to June 30th, 2006

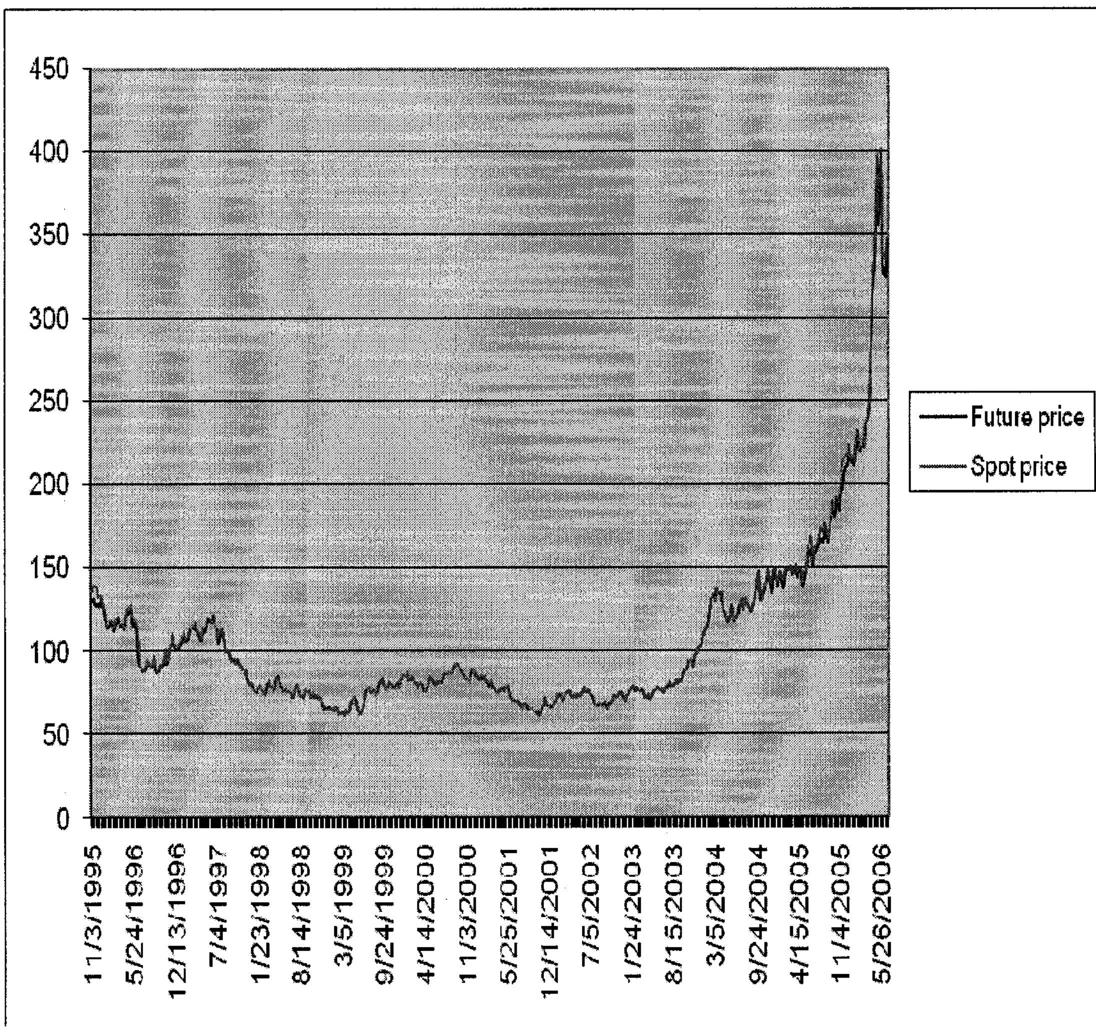

Figure 6 – Copper futures contract and Spot price from Jan 6th, 2006 to June 30th, 2006

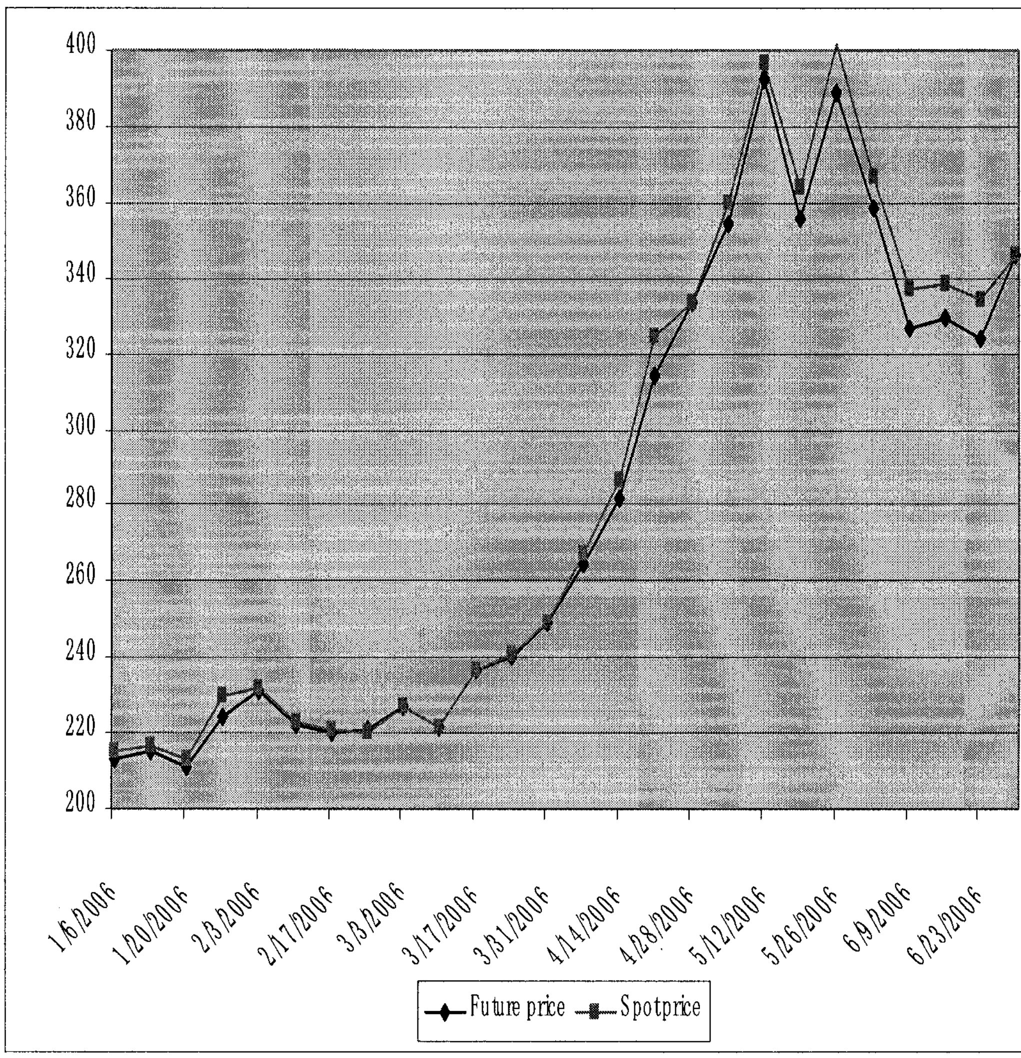

Figure 7 – Gold futures conditional standard deviation

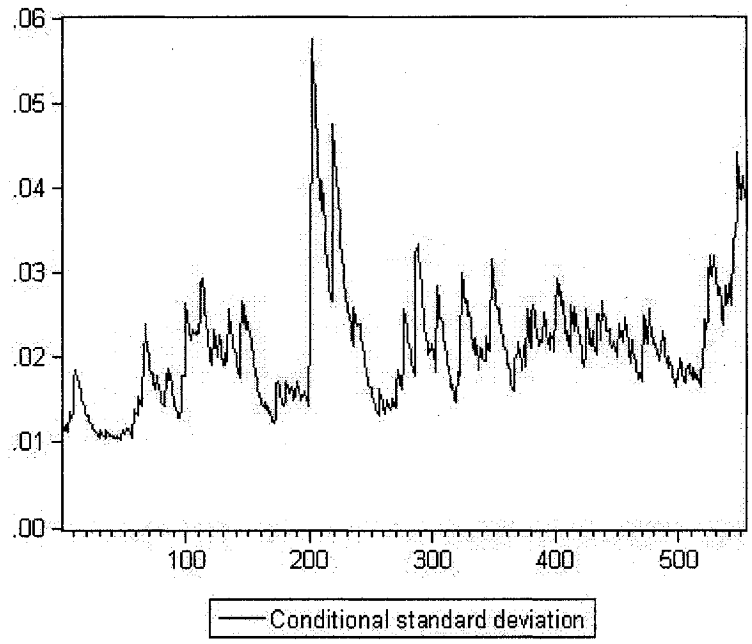

Figure 8 – Gold spot conditional standard deviation

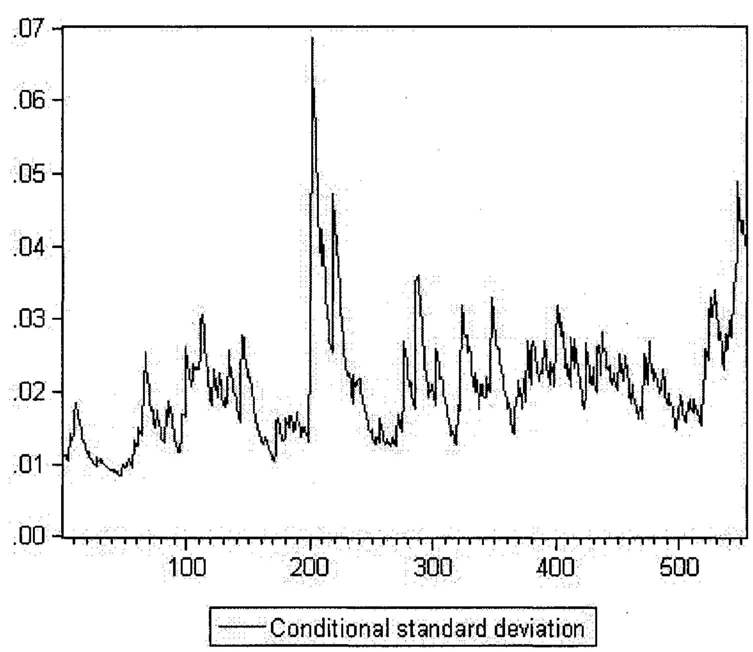

Figure 9 – Silver futures conditional standard deviation

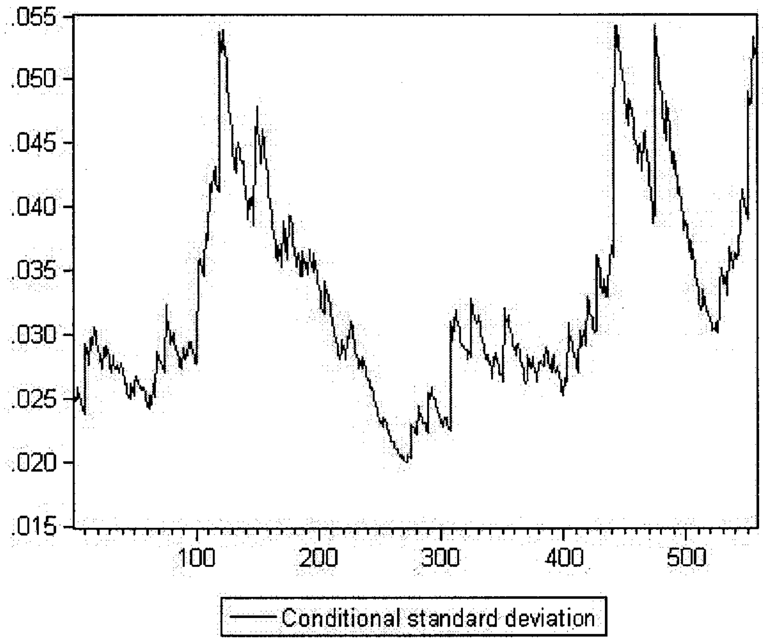

Figure 10 – Silver spot conditional standard deviation

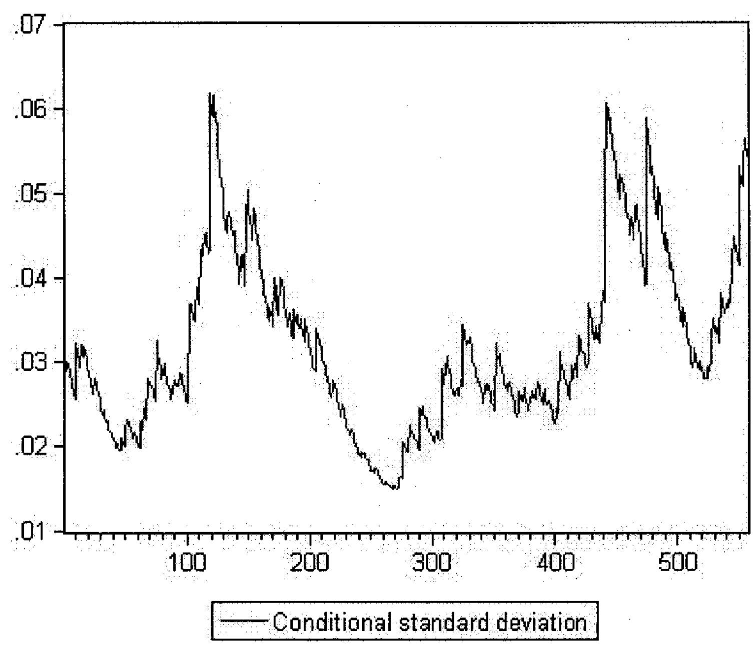

Figure 11 Copper futures conditional standard deviation

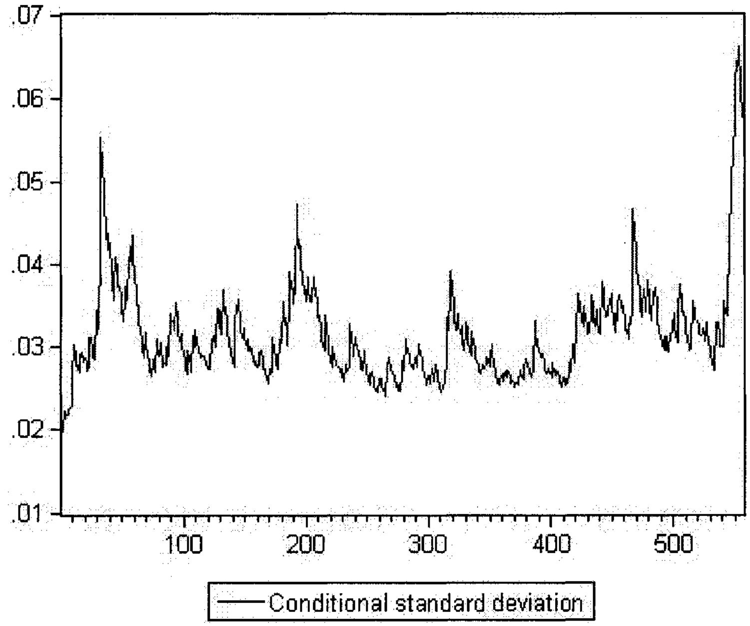

Figure 12 Copper spot conditional standard deviation

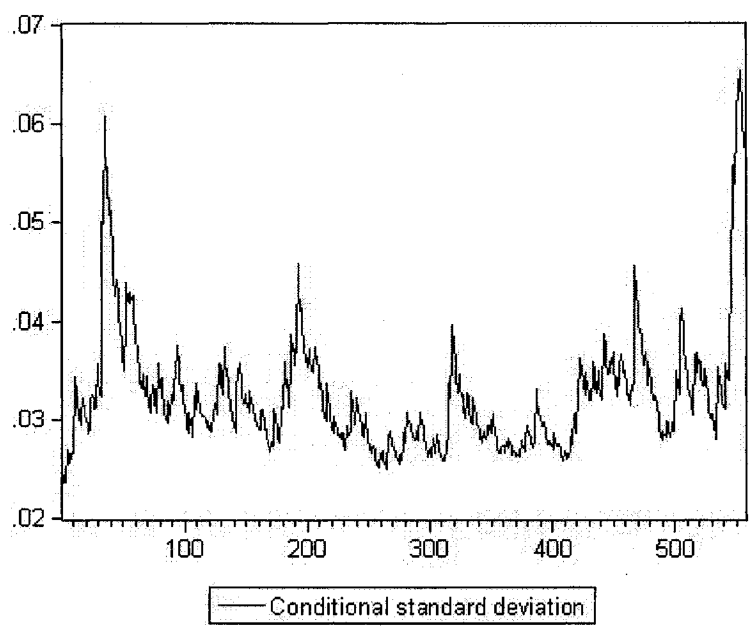

Table 1- Results of Fama's model for gold futures contracts

Estimation period: December 1995 - April 2006	a	b	Significance F
Regression (2):	0.8648	1.7745	0.5165
$S(T)-S(t)=a_1+b_1[F(t,T)-S(t)]+u(t,T)$	(0.8791)	(0.5165)	
Regression (3):	-0.8648	-0.7745	0.7767
$F(t,T)-S(T)=a_2+b_2[F(t,T)-S(t)]+z(t,T)$	(0.8791)	(0.7767)	

Note – P-values reported in parentheses.

Table 2- Results of Fama's model for silver futures contracts

Estimation period: November 1995 - March 2006	a	b	Significance F
Regression (2):	0.1403	0.0553	0.9829
$S(T)-S(t)=a_1+b_1[F(t,T)-S(t)]+u(t,T)$	(0.1499)	(0.9829)	
Regression (3):	-0.1403	0.9447	0.7149
$F(t,T)-S(T)=a_2+b_2[F(t,T)-S(t)]+z(t,T)$	(0.1499)	(0.7149)	

Note – P-values reported in parentheses.

Table 3- Results of Fama's model for copper futures contracts

Estimation period: November 1995 - April 2006	a	b	Significance F
Regression (2):	2.8239	-0.9230	0.1126
$S(T)-S(t)=a_1+b_1[F(t,T)-S(t)]+u(t,T)$	(0.0872)	(0.1126)	
Regression (3):	-2.8239	1.9230	0.0011
$F(t,T)-S(T)=a_2+b_2[F(t,T)-S(t)]+z(t,T)$	(0.0872)	(0.0011)	

Note – P-values reported in parentheses.

Table 4- Wald test results of Fama's model for gold

Estimation period: December 1995 - April 2006	a=0 and b=1	a=0	b=1
Regression (2): $S(T)-S(t)=a_1+b_1[F(t,T)-S(t)]+u(t,T)$	0.3155 (0.7306)	0.0233 (0.8791)	0.0811 (0.7767)
Regression (3): $F(t,T)-S(T)=a_2+b_2[F(t,T)-S(t)]+z(t,T)$	1.0943 (0.3412)	0.0233 (0.8791)	0.4259 (0.5165)

Note – F static reported. P-values reported in parentheses.

Table 5- Wald test results of Fama's model for silver

Estimation period: November 1995 - March 2006	a=0 and b=1	a=0	b=1
Regression (2): $S(T)-S(t)=a_1+b_1[F(t,T)-S(t)]+u(t,T)$	1.0894 (0.3429)	2.1263 (0.1499)	0.1347 (0.7149)
Regression (3): $F(t,T)-S(T)=a_2+b_2[F(t,T)-S(t)]+z(t,T)$	1.2757 (0.2866)	2.1263 (0.1499)	0.0005 (0.9829)

Note – F static reported. P-values reported in parentheses.

Table 6- Wald test results of Fama's model for copper

Estimation period: November 1995 - April 2006	a=0 and b=1	a=0	b=1
Regression (2): $S(T)-S(t)=a_1+b_1[F(t,T)-S(t)]+u(t,T)$	9.7405 (0.0001)	2.9724 (0.0872)	11.0855 (0.0011)
Regression (3): $F(t,T)-S(T)=a_2+b_2[F(t,T)-S(t)]+z(t,T)$	4.0000 (0.0207)	2.9724 (0.0872)	2.5540 (0.1126)

Note – F static reported. P-values reported in parentheses.

Table 7- Unit root test statistics for gold futures and spot series

Panel A: Price Levels

Series	ADF	DF-GLS	PP
Futures	1.068755	0.475008	1.599594
Spot	1.111481	0.506807	1.606863

Panel B: First Differences of Prices

Series	ADF	DF-GLS	PP
Futures	-21.53971	-1.821748	-21.48338
Spot	-21.24985	-18.84749	-21.12353

Note - The values reported in the table are the t-statistics (Adjusted t-statistics for PP). The 5% critical levels for ADF (Augmented Dickey Fuller), DF – GLS (Dickey Fuller detrended residuals), and PP (Phillips Perron) are -2.867, -1.94, and -2.87 respectively (MacKinnon (1996)).The AIC criterion was used (Max Lag Specified is 18).

Table 8- Unit root test statistics for silver futures and spot series

Panel A: Price Levels

Series	ADF	DF-GLS	PP
Futures	-0.154856	-0.001733	-0.429390
Spot	-0.258914	-0.121585	-0.229593

Panel B: First Differences of Prices

Series	ADF	DF-GLS	PP
Futures	-21.79682	-1.634205	-21.77567
Spot	-20.88958	-1.160861	-20.76534

Note - The values reported in the table are the t-statistics (Adjusted t-statistics for PP). The 5% critical levels for ADF (Augmented Dickey Fuller), DF – GLS (Dickey Fuller detrended residuals), and PP (Phillips Perron) are -2.867, -1.94, and -2.87 respectively (MacKinnon (1996)).The AIC criterion was used (Max Lag Specified is 18).

Table 9- Unit root test statistics for copper futures and spot series

Panel A: Price Levels

Series	ADF	DF-GLS	PP
Futures	4.395909	1.945778	3.136420
Spot	2.878695	1.432981	2.787780

Panel B: First Differences of Prices

Series	ADF	DF-GLS	PP
Futures	-11.05081	-10.64570	-23.88096
Spot	-10.82545	-6.234794	-24.51695

Note - The values reported in the table are the t-statistics (Adjusted t-statistics for PP). The 5% critical levels for ADF (Augmented Dickey Fuller), DF – GLS (Dickey Fuller detrended residuals), and PP (Phillips Perron) are -2.867, -1.94, and -2.87 respectively(MacKinnon (1996)).The AIC criterion was used (Max Lag Specified is 18).

Table 10– Johansen Co integration Tests of gold

Panel A: Johansen Cointegration Tests (Trace Statistics)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
r = 0 *	0.170207	103.5624	15.49471	0.0001
r ≤1	0.002401	1.317320	3.841466	0.2511

Panel B: Johansen Cointegration Tests (Max Statistics)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
r = 0 *	0.170207	102.2450	14.26460	0.0000
r ≤1	0.002401	1.317320	3.841466	0.2511

Panel C: Normalized cointegrating coefficients (standard error in parentheses)

Futures	Spot
1.000000	**-1.000967 (0.00074)**

Note – Trace test indicates 1 cointegrating equation at the 0.05 level. *denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values. Max-eigenvalue test indicates 1 cointegrating equation at the 0.05 level.

Table 11– Johansen Co integration Tests of silver

Panel A: Johansen Cointegration Tests (Trace Statistics)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
r = 0 *	0.048009	28.93274	15.49471	0.0003
r ≤1	0.003209	1.774267	3.841466	0.1829

Panel B: Johansen Cointegration Tests (Max Statistics)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
r = 0 *	0.048009	27.15847	14.26460	0.0003
r ≤1	0.003209	1.774267	3.841466	0.1829

Panel C: Normalized cointegrating coefficients (standard error in parentheses)

Futures	Spot
1.000000	**-0.988971 (0.00395)**

Note – Trace test indicates 1 cointegrating equation at the 0.05 level. *denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values. Max-eigenvalue test indicates 1 cointegrating equation at the 0.05 level.

Table 12– Johansen Co integration Tests of copper

Panel A: Johansen Cointegration Tests (Trace Statistics)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
r = 0 *	0.106038	73.47367	15.49471	0.0000
r ≤1	0.020794	11.59912	3.841466	0.0007

Panel B: Johansen Cointegration Tests (Max Statistics)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
r = 0 *	0.106038	61.87455	14.26460	0.0000
r ≤1	0.020794	11.59912	3.841466	0.0007

Panel C: Normalized cointegrating coefficients (standard error in parentheses)	
Futures	**Spot**
1.000000	**-0.977271 ((0.00343))**

Note – Trace test indicates 2 cointegrating equation at the 0.05 level. *denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values. Max-eigenvalue test indicates 2 cointegrating equation at the 0.05 level.

Table 13-Univariate GARCH (1, 1) Model Estimates

$$R_{st} = C_s + \varepsilon_t$$

$$R_{ft} = C_f + \varepsilon_t \text{, where } \varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma^2_{t-1}, v)$$

$$h_t = C_h + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1}$$

Part A: Gold	**Futures return**	**P-value**	**Spot return**	**P-value**
C_s, C_f	-0.000338	0.6423	-0.000611	0.3629
C_h	1.13E-05	0.0063	9.80E-06	0.0080
α_1	0.143786	0.0000	0.183031	0.0000
β_1	0.853554	0.0000	0.827344	0.0000
Log likelihood	1372.687		1389.745	

Part B: Silver	**Futures return**	**P-value**	**Spot return**	**P-value**
C_s, C_f	0.000470	0.7053	-0.000185	0.8658
C_h	1.64E-05	0.0275	1.00E-05	0.0353
α_1	0.055526	0.0001	0.077853	0.0000
β_1	0.933703	0.0000	0.919820	0.0000
Log likelihood	1126.482		1154.474	

Part C: Copper	**Futures return**	**P-value**	**Spot return**	**P-value**

C_s, C_f	0.000824	0.5076	0.000965	0.4575
C_h	6.11E-05	0.1465	6.32E-05	0.1342
α_1	0.093006	0.0008	0.085280	0.0009
β_1	0.851264	0.0000	0.859825	0.0000
Log likelihood	1143.532		1125.773	

Table 14 - Univariate GJR-GARCH Model Estimates

$R_{st} = C_s + \varepsilon_t$

$R_{ft} = C_f + \varepsilon_t$, where $\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_{t-1}^2, \nu)$

$h_t = C_h + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 \varepsilon_{t-1}^2 I_{t-1}$, where $I_{t-1} = \begin{cases} 0, \varepsilon_{i,t} \geq 0 \\ 1, \varepsilon_{i,t} \prec 0 \end{cases}$

Part A: Gold	Futures Series	P-value	Spot Series	P-value
C_s, C_f	0.000415	0.5964	0.000220	0.7636
C_h	1.73E-05	0.0000	1.56E-05	0.0001
α_1	0.213809	0.0000	0.265498	0.0000
γ_1	-0.171684	0.0000	-0.202192	0.0000
β_1	0.847005	0.0000	0.821082	0.0000
Log likelihood	1377.979		1396.130	

Part B: Silver	Futures Series	P-value	Spot Series	P-value
C_s, C_f	0.002045	0.1118	0.001267	0.2688
C_h	1.85E-05	0.0079	1.62E-05	0.0019
α_1	0.114976	0.0001	0.159145	0.0000
γ_1	-0.134814	0.0000	-0.168705	0.0000
β_1	0.941201	0.0000	0.916591	0.0000
Log likelihood	1138.535		1167.632	

Part C: Copper	Futures Series	P-value	Spot Series	P-value

C_s, C_f	0.001306	0.3062	0.001520	0.2512
C_h	7.43E-05	0.1164	8.45E-05	0.0840
α_1	0.132350	0.0055	0.133048	0.0020
γ_1	-0.092504	0.0457	-0.101516	0.0262
β_1	0.842876	0.0000	0.841032	0.0000
Log likelihood	1146.146		1128.937	

Table 15- Out-of-Sample Hedging Results Measured by Relatively Percentage Variance Reduction

Hedging Effectiveness	Naïve	OLS	Symmetric bivariate GARCH	Asymmetric bivariate GARCH
Gold	0.97966688	0.979539	0.9841127	0.97945011
Silver	0.982622283	0.983061597	0.984080866	0.981655276
Copper	0.938679	0.93817431	0.959454455	0.941445466

Table 16- Average Hedge Ratio

Metals	OLS	Symmetric bivariate GARCH	Asymmetric bivariate GARCH
God	0.981933667	1.016344	1.028700667
Silver	0.987254333	0.986049333	0.994947
Copper	0.944829667	0.909012333	0.989431667

Table 17- Correlation between futures and spot return

Metals	Correlation between futures and spot return
Gold	0.99077471
Silver	0.994348501
Copper	0.950846106