

Investigating the Long time Memory in the Future Market of Gold

Mohsen Mehrara¹, Nafiseh Behradmehr², Mitra Saboonchi³

Abstract

This paper concentrates on investigating the long memory property of the gold future markets in the United States. The data set consists of daily future prices, and long memory tests based on ARFIMA with use of three quantitative methods: Non Linear least Square (NLS), Modified Profile Likelihood (MPL) and Exact Maximum Likelihood (ML). The results of the ARFIMA model don't show strong evidence of long memory, but it implies short memory. So prices follow a predictable behavior, which is inconsistent with the efficient market hypothesis. The evidence of short memory in prices, however, shows that uncertainty or risk is an important determinant of behavior of daily future prices in the gold future market of the United States.

Keywords: ARFIMA, Efficiency, Long memory, gold Future market

JEL Classification: C22, C58

1. Introduction

The effectiveness of the basic capital resource allocation function of a financial market depends on the maturity degree of the market. "Market efficiency" is one of the metrics to evaluate the maturity degree of the market (Huiwen Zou, 2011). The market efficiency can be differently understood based on different standing points that one of them is the information efficiency (Fama, 1970). If the time series of asset price like gold follow a martingale, that is relaxed version of the random walk, then its return is purely non- predictable and investors are unable to make abnormal returns consistently over time. Hence, the question as to whether assets prices follow a martingale sequence has strong implications to the market efficiency in the weak form (Jae. H. Kim). The most popular statistical tool to test for the martingale hypothesis is the variance ratio (VR) test , which has been adapted by the most of past studies , that originally proposed by Lo and Mackinlay (1988) . Weak form market efficiency implies that the price time series, say $\{P_t\}_{t=0}^T$, does not exhibit serial correlation , or "memory".

The main goal of this paper is to examine the efficiency by investigating the Martingale behavior of prices in the gold future market of the U.S. We estimate Auto Regressive Fractionally Integrated Moving Average (ARFIMA) models to examine the existence of long memory in this market.

This paper is organized as follows: In section 2 we present a brief summary of previous work on long –memory processes in economics. In section 3 we provide a more technical discussion of ARFIMA model. In section 4 we give a summary of the data set and report the empirical results and section 5 is devoted to conclusions.

2. Literature review

The concept of long memory was introduced by the British hydrologist Hurst (1951). Early contributions to the subject of long memory in time series are those by Mandelbrot (1971), Geweke and Porter – Hudak (1983) and Hosking (1981). Granjer and Joyeux (1980) introduced fractionally integrated ARMA models, which were more recently discussed by Sowell (1992), Beran (1992) and Baillie (1996). The finding of long-term dependence in financial data might be in contradiction to the Efficient Markets Hypothesis of Fama (1970), the first contribution to this subject in finance is that by Greene and Fielitz (1977) who, by mean of the rescaled range (R/S) method of Hurst, found long memory in daily equity returns. Spot and futures foreign – exchange rates and commodity prices were investigated with respect to long memory were investigated with respect to long memory. Contributions by Helms et al (1984) , Cheung

¹ Faculty of Economics, University of Tehran, Tehran, Iran

² Faculty of Economics, University of Tehran, Tehran, Iran

³ University of Tehran, Tehran, Iran

and Lai (1993), Fang et al (1994) and Barkoulas et al (1997) confirm long memory in the above – mentioned kinds of foreign –currency rates. Koop et al (1997) provide a Bayesian analysis of ARFIMA models and describe a test of ARFIMA alternatives. In the next section we explain in detail the nation of long memory process.

3. Methodology

Long- Memory Process

Given a discrete time series , Y_t , with autocorrelation function P_j , at lag j , the process Y_t is said to be integrated of order d , if $(1-L)^d Y_t = U_t$, where U_t is the residual term . For $0 < d < 0.5$, the process is characterised as long memory since its autocorrelations are all positive and decay at a slow rate. For $-0.5 < d < 0$, the sum of absolute values of autocorrelations tends to a constant, thus the process has a short-memory (Baillie, 1996).

In the long-memory process, a shock at time t , continues to influence future Y_{t+k} for a longer horizon, k , than would be the case for the standard stationary ARMA process (Onour , 2010) .

The ARFIMA Process

The ARFIMA (p, d, q) model can be stated as :

$$\Phi(L) (1 - L)^d (Y_t - \mu) = \Theta(L) \varepsilon_t \tag{1}$$

Where

$$\Phi(L) = \sum_{j=1}^p \Phi_j L^j \ ; \ \Theta(L) = \sum_{j=1}^q \Theta_j L^j ,$$

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k - d) L^k}{\Gamma(k + 1) \Gamma(-d)}$$

And L is the lag operator, d is the fractional differencing parameter, all roots of $\Phi(L)$ and $\Theta(L)$ assumed to lie outside the unit circle , and ε_t is white noise .

4. Data and Empirical Results

Data Analysis

Data employed in this study are daily Future prices of gold market for United States in New York Mercantile exchange (NYMEX). The sample period covers from 2 January 1998 to 13 May 2011. In this study we use log-scale data instead of row data. Because after using lags, series tend to be characterized by normal distribution and it help us to decline the noise level of data. Summary statistics for log-price series are presented in Table1:

Table 1: Summary Statistics

No. of observation	3352
Mean	6/181757
Standard deviation	0/535863
Skewness	0/532263
Kurtosis	1/891802
Minimum	5/532599
Maximum	7/340187
J-B	329/7978

Note: Significant at 5% level

Excess Kurtosis statistic indicates that the log of prices tend to have a shorter peak and fatter- tail distribution than a normal distribution. The negative skewness result implies a higher probability for prices to decline. The Jarque-Bera (JB) test statistic provides evidence to reject the null-hypothesis of normality for the distribution of log-prices.

Empirical Results

Variance Ratio Test

Table 2 presents the variance ratios based on the daily values of the gold Future market. Also shown are the corresponding Z statistics for the null hypothesis that ratio has a value of 1. If the data support the random walk hypothesis, the VR(q)s have values close to 1 for the values of q assigned .

Table 2: The Variance ratio test

	$q = 2$	$q = 4$	$q = 6$	$q = 8$	$q = 10$
VR(q)	1/051529	0/696329	0/683617	0/781922	0/753084
Z(q)	1/764123	-6/202527	-5/326943	-3/151551	-3/097980

Note: Significant at 5% level

In $q=4, 6, 8$ and 10 the test statistics $Z(q)$, are small enough to reject the hypothesis that results obtained , don't provide strong support that the log of prices follow a random walk . It is not consistent with the efficient market hypothesis .thus, the log – prices in the gold Future market can be predicted and may move in trend. So we investigated the existence of memory in this market.

Before analyzing the long memory in prices, we test whether or not the log-price series is a stationary process using the Augmented Dicky- Fuller Test or ADF unit root tests. The null hypothesis of the ADF test is that a time series contains a unit root. The results of this test are reported in Table 3.

Table 3: Unit Roots tests results

ADF test with time trend	LPGOLD	First differenced of LPGOLD
Critical Value	1/998041	-56/34642
Test Statistic	0/9895	0/001
Significant level	%5	%5

The results of the ADF unit root test don't support the rejection of the null hypothesis of a unit root at the conventional significance levels. Hence, the price series is not stationary and needs to be differenced to make it stationary that is suitable for the long memory tests.

Long Memory in Prices

The estimation results and diagnostic statistics of the ARFIMA(p,d,q) models are reported in Table 4. We estimate different specifications of the ARFIMA(p,d,q) with $p=0, 1, 2$ and $q=0, 1, 2$ for log – price series . A conventional model selection criterion, the Akaike's Information Criterion (AIC), is used to choose the best model that describes the data. We use three techniques in estimating the “Memory Parameter”, that are: Modified Profile Likelihood (MPL) , Non Linear Least Square (NL) and Exact Maximum Likelihood (ML). The preferred model for the log - price series is the ARFIMA(1 , d ,1).

Table 4: Estimation of d parameter results

ARFIMA (p,d,q)	\hat{d}	P-Value	Log - Likelihood	AIC
ARFIMA(1,d,1) (ML)	-0/210922	0/000	10080/2455	-6/16411471
ARFIMA(1,d,1) (NLS)	-0/204777	0/000	10080/6729	-6/16437622
ARFIMA(1,d,1) (MPL)	-0/199651	0/000	10061/7302	-6/15278693

Note: Significant at 5% level

The results indicate that the long memory parameter (d) is significantly different from zero . ARFIMA(1 , d ,1) results in Table 4 support the evidence that log -prices of the gold Future market exhibit short – memory behavior . The point estimate of \hat{d} is negative ($- 0.5 < \hat{d} < 0$) and significant at %5 level , for the three methods , indicating evidence of short – memory behavior of market . The sign and size of the \hat{d} parameter support the evidence that shocks are not likely to persist for long period in this market. According to (AIC), the best estimation of \hat{d} parameter is (-0.2) given by

(NLS) method. Table 5 presents results of ARFIMA(1 , -0.2 , 1) carried out using NLS method in Ox-metrics programming procedure .

Table 5: ARFIMA (1, -0.2 , 1)

Variable	Coefficient	Standard-error	t- statistic	Prob
<i>C</i>	0.0003	0.0049	5.30	0.000
<i>d-ARFIMA</i>	-0/2047	0.0487	-4.20	0.000
<i>AR(1)</i>	0.7373	0.4317	17.1	0.000
<i>MA(1)</i>	-0.5405	0.0485	-11.1	0.000

Note: Significant at 5% level

5. Conclusion

In this paper, we have investigated the weak form of efficiency and the long memory properties of log- prices of the gold Future market in NYMEX for United States. We empirically evaluated whether selected prices follow the Martingale sequence. This exercise is important because the Martingale property has strong implications to the market efficiency. Then price series was modeled using an ARFIMA model. Time series data from 2 January 1998 to 13 May 2011 are considered in this paper. The Martingale hypothesis for gold Future market has been soundly rejected, indicating that this market has been inefficient in the weak form. The results of the estimated ARFIMA model don't show the existence of long memory in log-price series. The estimation of the long memory parameter suggests that the price series is a short memory process. This implies that a shock to market is not likely to persist for long period, and future prices can be better predicted using most recent lagged prices .Evidence of stationary short memory in prices has important implications for investors as well as for policy makers. Since persistence in prices could represent market inefficiency, it could be exploited by international investors to earn excess returns .The findings of the paper also show that the effect of shock volatility tends to dissipate within a short period of time. This implies that excessive volatility in this market should not be regarded as a long-term phenomenon.

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