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On the Predictability and Resilience of Gold Prices' Returns and Volatility

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Abstract

Utilizing forty-five years of daily London gold price fixes, this paper finds the presence of dual long-memory processes in the 10:30am fix and the 3:00pm price fix utilizing ARFIMA-FIGARCH and ARFIMA-FIEGARCH models, respectively. This research proves that the return and volatility of the London Gold price fixes have predictable structures and does not conform to the weak-form efficient assumption of Fama (1970). This study also suggests that the London gold price fixes do not exhibit leverage effects and asymmetric volatility response properties. This means that gold as an investment is generally immune to negative shocks, proving the resilience of gold as financial instrument. This paper also reveals the ARFIMA-FIAPARCH models have better fit in modeling the morning gold fix, while the ARFIMA-FIEGARCH model is more suitable in modeling the afternoon gold fix.

JEL classification numbers: G10, G12
Keywords: long-memory and asymmetry, fractionally-integrated models, London Gold price fix returns and volatilities.

1 Introduction

Historically, gold has been perceived by investors as a safe-haven asset expected to retain or even increase its value in periods of stock market declines and recession. Gold as an investment is sought to minimize exposure to huge losses and hedge against risks. However, this reputation is being challenged in recent history, because gold is experiencing the biggest sell off in the last three

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decades. The dramatic fall in gold prices is being perceived as a bubble deflation caused by more speculative share-dealing bets, which helped in boosting the volatility of gold prices.

The London gold fix mechanism determines gold prices. Value fixing is done twice each business day, first at 10:30am or the morning fix; and second at 3:00pm or the afternoon fix. This determined price is utilized by 1) large gold owners like refineries and mining companies and central banks; 2) retailers like coin dealers and jewelry manufacturers; and 3) derivatives markets like futures, swaps and options. This mechanism fixes a gold price to settle contracts between members of the London bullion market, and to provide a recognized rate as a benchmark for pricing gold products and derivatives around the world. Most gold producers and refiners sell using the afternoon fix, because it is timelier in their business hours and reflects market conditions more due to its liquidity, and because Asia and North American markets are closed during the morning fix.

Comprehending return and volatility characteristics of gold is crucial because the persistent changes in their structure as an investment can expose both hedgers and speculators to risks. Traders and investors noticed that the London gold 10:30am fix is generally higher than the 3:00pm fix, thus, a possible difference in the long-memory and asymmetric volatility properties of the morning and afternoon gold fix prices can be possible. The prediction of gold's return and volatility has attracted greater interest to investors and researchers recently because of its longstanding reputation of stability is being rigged. The notion that whether or not gold is still a resilient investment and much more predictable have been more relevant in the recent times. This study plans to capture these tendencies through determining the long-memory process and asymmetric volatility property of gold fix prices.

Long-memory process models the presence of a persistent positive dependence among distant observations, which suggests the predictability of gold prices' time-series in returns and volatility. On the other hand, the asymmetric volatility property of gold prices describes the negative correlation between returns and changes in volatility. This process is connected to the leverage effects property, wherein negative shocks often result to future higher volatility rather than positive shocks. These nonlinear processes perfectly test whether gold fix prices is still efficient and resilient to shocks. The literature of gold time-series was studied by Frank and Stengos (1989), Yang and Brorsen (1993), and Habibnia (2010), and all agreed on the existence of nonlinear deterministic process in its structure. Cheung and Lai (1993) studied the predictable behavior of gold during the post-Bretton Woods period, and found that long-memory property of gold returns is unstable, and with few observations used little evidence of long-memory can be found. In a more recent set of studies, Wang et al. (2007) proved that the prediction of gold prices is possible given the proper modeling to forecast the relative error of the utilized GM and Markov chain. This was also proven by Ismael et al. (2009) by using the multiple regression method, and suggested macroeconomic variables to predict gold prices. On the resilience of gold as investments, Baur and Lucey (2010) find that gold is a good hedge against stocks, and a safe haven in extreme stock market conditions. A related study of Baur and McDermott (2010) showed a particular example wherein gold has reduced losses in the peak of the recent financial crisis.

The study is motivated by the recent surge in the application of fractionally-integrated long-memory and asymmetric volatility models in financial time-series. This research is also motivated in adding to the literature of gold prices returns and volatility, particularly statistically establishing its predictable and resilient properties as an investment. This research contributes to the literature by comparing four combinations of fractionally-integrated models, a) ARFIMA, b) ARFIMA-FIGARCH, c) ARFIMA-FIAPARCH, and d) ARFIMA-FIEGARCH in examining long-term positive dependence, asymmetry and leverage effects in the returns and volatility of London gold fix price returns. In relation with the motivation and contributions, this paper differs from the previous studies through these four main objectives:

a) identify which type of models are better to characterize future values using lagged returns to determine the time-series of morning and afternoon gold fixes;

b) find out positive long-term dependence in the time-series of gold fix prices, and examine the dual long-memory process in their returns and volatilities;

c) determine differences in the characteristics of the 10:30am and 3:00pm price fixes with regards to their short-, intermediate-, and long-memory processes;

d) challenge the basic assumptions of the EMH of Fama (1970), because the presence of high-order positive correlations make predictions on future returns possible

The research is written as follows. Section 2 explains the data and the four fractional integration models applied; Section 3 presents the empirical results; and Section 4 gives the conclusion.

2 Data and Methodology

This research analyzes daily closing prices of the London Gold fix from the Federal Reserve Bank of St. Louis database from April 2, 1968 to May 16, 2013. The 10:30 morning fix has a total of 11,387 observations, and the 3:00 afternoon fix has a total of 11,256 data points. The difference in the number of observations is the absence of gold fix price on certain dates. The series of returns were computed as, $y_t = 100(\log p_t - \log p_{t-1}),$ where p_t represents the price at time t. The financial time-series data were modeled by ARFIMA-FIGARCH, ARFIMA-FIEGARCH and ARFIMA-FIAPARCH processes and are explained below.

The ARFIMA model as proposed by Granger and Joyeux (1980) and Hosking (1981) provides the first testing of the long-memory property of time-series data. The model introduces the difference parameter (d) as a non-integer and suggests the fractionally integrated process $I(d)$ in the conditional mean. The ARFIMA (p, d, q) model satisfies both stationary and invariability conditions and can be written as:

$$\phi(L)(1-L)^d(X_t - \mu) = \theta(L)\varepsilon_t, \tag{1}$$

$$\varepsilon_t = z_{t\sigma_{t'}} \qquad z_t \sim N(0.1),$$

where *d* represents a fractional integration real number parameter, μ denotes the conditional mean, L corresponds to the lag operator and ε_t represents a white noise residual. The $(1-L)^d$ denotes the fractional differencing lag operator. The AR and the MA processes are assumed to have all roots outside the unit circle, and can be shown as $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_P L^p$
and $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - ... - \theta_P L^p$, respectively.

The ARFIMA model is assumed to be stationary when $-0.5 < d < 0.5$, where the effect of shocks to ε_t decays at a gradual rate to zero. Also, the model has a short memory when $d = 0$, where the effect of shocks decays geometrically; and a unit root process is exhibited when $d=1$. The model has a long-memory process or has positive dependence among distant observations when $0 < d < 0.5$; and is also consistent to an intermediate memory or has antipersistent property when $-0.5 < d < 0$. Moreover, the ARFIMA model becomes non-stationary when $d \geq 0.5$; and stationary but a noninvertible process when $d \leq -0.5$, which makes the data time-series impossible to model by any AR process.

The FIGARCH model as proposed by Baillie et al. (1996) improves the traditional GARCH model allows the distinguishing parameter (*d*) to be a non-integer, which accounts the fractional integration in the model. The FIGARCH process also offers flexibility by capturing short-, intermediate- and long-memory in the volatility of financial time-series. The FIGARCH (p, d, q) model can be expressed as:

$$\left[\phi(L)(1-L)^d\right]\varepsilon_t^2 = \omega + [1 - \beta(L)](\varepsilon_t^2 - \sigma_t^2), \tag{2}$$

where *d* denotes a fractional integration parameter, L corresponds to the lag operator and ε_t denotes a white noise residual process. The FIGARCH model assumes a long-memory process when $0 < d < 1$ allowing more flexibility in modeling the conditional variance; $(1-L)^d$ represents the fractional differencing operator; and $\phi(L)$ denotes an infinite summation which, has to be truncated. The FIGARCH process is reduced to the GARCH model when $d = 0$.

The FIEGARCH model as proposed by Baillie et al. (1996) extends the EGARCH model, which also determines long-memory in the conditional variance.

Similar to the EGARCH, the FIEGARCH model can also capture volatility asymmetry found in the financial time-series. The FIEGARCH (p, d, q) model can be expanded as follows:

$$y_t = \sigma_t \varepsilon_t,$$

$$(1-\phi L)(1-L)^d \log(\sigma_t^2) = \omega + g(\varepsilon_{t-1}), \tag{3}$$

where d represents the fractional integration parameter which captures the long-memory property when $0 < d < 1$. A significant negative parameter theta (θ) measures the leverage effect, which signifies strong volatility persistence, while $g(\varepsilon_t) = \alpha(|\varepsilon_t| - \sqrt{\frac{2}{\pi}}) + \theta\varepsilon_t$ and ε_t is a Gaussian white noise with variance 1. The FIEGARCH model can become the short-memory EGARCH model of Nelson (1991) when $d = 0$; and the process is stationary if $|\phi| < 1$ and $|d| < 0.5$.

The FIAPARCH model as proposed by Tse (1998) captures volatility asymmetry aside from the long memory feature in the conditional variance. The model is seen to be superior than the FIGARCH process through the improvement in volatility with the function $(|\varepsilon_t| - \gamma\varepsilon_t)^\delta$ and can be expressed as follows:

$$\sigma_t^\delta = \omega[1-\beta(L)]^{-1} + \{1 - [1-\beta(L)]^{-1}\rho(L)(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^\delta, \tag{4}$$

where d represents the fractional integration parameter, and gamma (γ) denotes the asymmetry model parameter. The FIAPARCH model has a long-memory process when $0 < d < 1$. The model shows that negative shocks have more impact on volatility than positive shocks when $\gamma > 0$, and the inverse is also the same. The FIAPARCH process can be also reduced to the FIGARCH model if $\gamma = 0$ and $\delta = 2$.

3 Empirical Results

Table 1 shows that the London gold fix prices have positive returns with the 10:30am fix slightly higher with 0.013 than the 3:00pm fix with 0.012. The morning fix is also more volatile with 0.562 compared to 0.545 of the afternoon fix. The research concludes that the Modern Portfolio Theory of Markowitz (1952), stating that a higher risk is compensated with higher returns is consistent with the London gold fix time-series. Both gold fix returns are positively skewed and have leptokurtic distributions. The Jarque-Bera statistic for residual normality shows that the gold fix returns are under a non-normal distribution assumption.

Table 2 illustrates the use of Augmented Dickey-Fuller test to examine the stationarity of the London gold morning and afternoon price fixes, and the minimum value of the Akaike Information Criterion to identify the orders of the models. Both the 10:30am and 3:00pm return samples have no serial correlation, based on the results of the Lagrange Multiplier (LM) test. This paper used the ARCH-LM process to test the ARCH effect and eliminate heteroscedasticity in the volatility of the data, the test also illustrates that the GARCH models can be applied in the both the morning and afternoon fixes.

Table 3 shows the results for both ARFIMA and ARFIMA-FIGARCH models. The ARFIMA model finds no significant results on the long-memory structures of both the morning and afternoon price fixes. However the combined ARFIMA-FIGARCH models find long-memory processes in the returns of the 10:30am fix with 0.029 value significant at the 10% level. This paper also finds positive dependence the volatilities of both 10:30am fix with 0.521 value; and the 3:00pm fix with 0.489 value, both significant at the 1% level. This means that return and volatility of the London Gold price fixes have predictable structures and not a weak-form efficient financial time-series, which can signify a more predictable structure particularly for the morning fix. The 10:30am gold fix is seen to be steadier with less volatility caused by lower liquidity. These finding solidify the initial observations of Cheung and Lai (1993), Wang et al. (2007) and Ismail et al. (2009) in the predictable properties of gold. The log-likelihood value consistently points to the combined ARFIMA-FIGARCH models as the best fitting model to characterize the London Gold price fix compared to just utilizing the ARFIMA model.

The ARFIMA-FIEGARCH and ARFIMA-FIAPARCH models are also applied to confirm these initial findings and to add features of leverage effects and asymmetric volatility properties, respectively. Table 4 shows that the two models agree on the long-memory properties in the volatility of both the morning and afternoon fixes. However, only the ARFIMA-FIEGARCH models find positive dependence on the return of the 3:00pm price fix, which signifies dual long-memory in both returns and volatilities of the afternoon fix.

This research also discovers that the London Gold price fixes do not exhibit leverage effects with the significant positive value of the theta (θ) parameter. This is clearly supported by the negative gamma (γ) coefficients, which means that asymmetric volatility response to shocks is not present. This paper found that positive and negative news has the same magnitude and proves the resilience of gold as investment instrument. These findings are consistent to the initial claims of Baur and Lucey (2010) Baur and McDermott (2010) on the resistance of gold to extreme shocks and its safe haven property. This research used the highest log-likelihood values to identify the best fitting model. This study finds that the combination of the ARFIMA-FIAPARCH models are better in characterizing the morning gold fix, while the ARFIMA-FIEGARCH model is more suitable in modeling the afternoon gold fix. This paper provides technical evidence on gold's predictable property, and supports the old reputation of gold as a safe haven, which suggests that hedgers and speculators can depend on the resilience of gold as an investment to external shocks.

4 Conclusion

Identifying the gold price's predictability through the long-memory process, and resilience through the asymmetric volatility and leverage effects properties in returns and volatilities have long been a great interest for traders and investors. The combined ARFIMA-FIGARCH models find long-memory processes in the returns of the 10:30am fix, while the ARFIMA-FIEGARCH models find the same results on the return of the 3:00pm price fix. All fractionally-integrated models in the conditional variance agree on the long memory properties in the volatility of both the morning and afternoon fixes. This study also concludes that dual long-memory processes are present on the 10:30am fix and the 3:00pm price fix using ARFIMA-FIGARCH and ARFIMA-FIEGARCH, respectively. These initial results mean that return and volatility of the London Gold price fixes have predictable structures and does not conform to the weak-form efficient assumption of Fama (1970). Traders expect to experience abnormal returns given the right forecast modeling that they will employ. Using the highest log-likelihood values, this study finds the ARFIMA-FIAPARCH models to better characterize the morning gold fix, while the ARFIMA-FIEGARCH model is more suitable in modeling the afternoon gold fix. This paper also reveals that the London gold price fixes do not exhibit leverage effects and asymmetric volatility response, which means that negative shocks have similar effects with positive shocks contrary to most investments. The paper proves the resilience of gold as financial instrument, which suggests that investors can depend on the long-term viability of gold against external shocks.

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Table 1: The Sample Size and Period of the London Gold price fixing

London Gold price fix returns	**Start of Data**	**Obs.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**J-Bera**
Morning London Gold Price Fix (10:30am)	April 2, 1968	11,347	0.013	0.562	0.056	13.471	85,805***
Afternoon London Gold Price Fix (3:00pm)	April 2, 1968	11,216	0.012	0.545	0.062	10.949	56,028***

Source: Yahoo Finance; http://www.yahoo.com/finance.
Note: *, ** and *** are significance at 10, 5 and 1% levels.

Table 2: Summary Statistics of ARMA and GARCH filtering

Gold fixes	**ADF**	**ARMA**	**AIC**	**LM test**	**ARCH-LM**	**GARCH**	**AIC**	**ARCH-LM**
10:30am	-111.743***	(1,1)	1.684	1.353	691.898***	(1,1)	1.164	1.792
	(0.000)			(0.259)	(0.000)			(0.167)
3:00pm	-61.017***	(1,1)	1.625	1.852	780.549***	(2,2)	4.669	0.749
	(0.000)			(0.116)	(0.000)			(0.473)

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 3: Summary Statistics of ARFIMA and ARFIMA-FIGARCH models

	ARFIMA				ARFIMA-FIGARCH				
Gold fixes	**d-ARFIMA**	**ARCH**	**AIC**	**log-likelihood**	**d-ARFIMA**	**ARCH**	**d-FIGARCH**	**AIC**	**log-likelihood**
10:30am	0.011	(0,1)	1.683	-9547.085	0.029*	(2,1)	0.521***	1.143	-6478.230
	(0.359)				(0.076)		(0.000)		
3:00pm	0.018	(1,2)	1.625	-9105.365	0.020	(1,2)	0.489***	1.109	-6208.670
	(0.170)				(0.258)		(0.000)		

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 4: Summary Statistics of ARFIMA-FIEGARCH and ARFIMA-FIAPARCH models

	ARFIMA-FIEGARCH						ARFIMA-FIAPARCH					
Gold fix	**d-ARFIMA**	**ARCH**	**d-FIGARCH**	**theta**	**AIC**	**log-likelihood**	**d-ARFIMA**	**ARCH**	**d-FIGARCH**	**gamma**	**AIC**	**log-likelihood**
10:30am	0.007	(1,2)	0.477***	0.041***	1.140	-6457.44	0.007	(2,1)	0.467***	-0.127***	1.129	-6394.31
	(0.793)		(0.000)	(0.002)			(0.725)		(0.000)	(0.000)		
3:00pm	0.028*	(2,2)	0.560***	0.030***	1.099	-6154.205	0.014	(2,2)	0.444***	-0.102***	1.103	-6172.329
	(0.090)		(0.000)	(0.000)			(0.444)		(0.000)	(0.000)		

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.