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Volatility of Futures Contract in Iran Mercantile Market

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Abstract

Most financial theories are relying on estimation of volatility. Volatility is not directly observable and must be estimated. In this research we investigate the volatility of gold, trading as a futures contract on the Iran Mercantile Exchange (IME) using intraday (high frequency) data from 5 January 2009 to May 2012. This paper uses several models for the calculation of volatility based on range prices. The results show that a simple measure of volatility (defined as the first logarithmic difference between the high and low prices) overestimates the other three measures. Comparing values of RMSE, MSE, MAD and MAPE we find out that Garman-Klass and Rogers-Satchell Models are more accurate estimator of volatility.

Keywords: volatility, range-based models, futures contracts

1. Introduction

Volatility in financial markets has attracted growing attention in last decade as it is a measurement of risk and most important factor in pricing of new financial instruments (such as derivatives). Financial volatility is not observable variable therefore should be estimated by historical price. There are several reasons for such a growing attention in last decade to find the most accurate and consistent estimator of volatility; First of all, measurement of volatility has a lot of application in finance such as derivative products pricing, risk evaluation and hedging, value at risk, and portfolio allocation. With development of new financial instrument like derivatives we have to estimate volatility.

Moreover, financial statements such as income statement and balance sheets -which should be audited- give some information about different variable of next financial year but volatility of underlying stock or commodity is neglected and should be estimated separately.

It is now well known that volatility is time-varying and historical volatility estimated as the sample standard deviation of returns- closing price estimator- is not efficient and Estimators based on daily close data is imprecise. Essentially, Estimator based on daily close data is imprecise because they are constructed with the data of closing prices and might neglect the important intraday information of the price movement. For example, when today's closing price equals to last day's closing price, the price return will be zero, but the price variation during the today might be turbulent.

A significant practical advantage of the price range is that for many assets, daily opening, highest, lowest, and closing prices are readily available. Most data suppliers provide daily highest/lowest as summaries of intra-day activity. In fact, the range has been reported for many years in major business newspapers through so-called ''candlestick plots''. They are easy to implement as they only require the readily available high, low, opening and closing prices.

Some study demonstrated that the measurement noise in daily squared returns is too high for observing the true underlying volatility process (Andersen 1996; Bollerslev 1986).

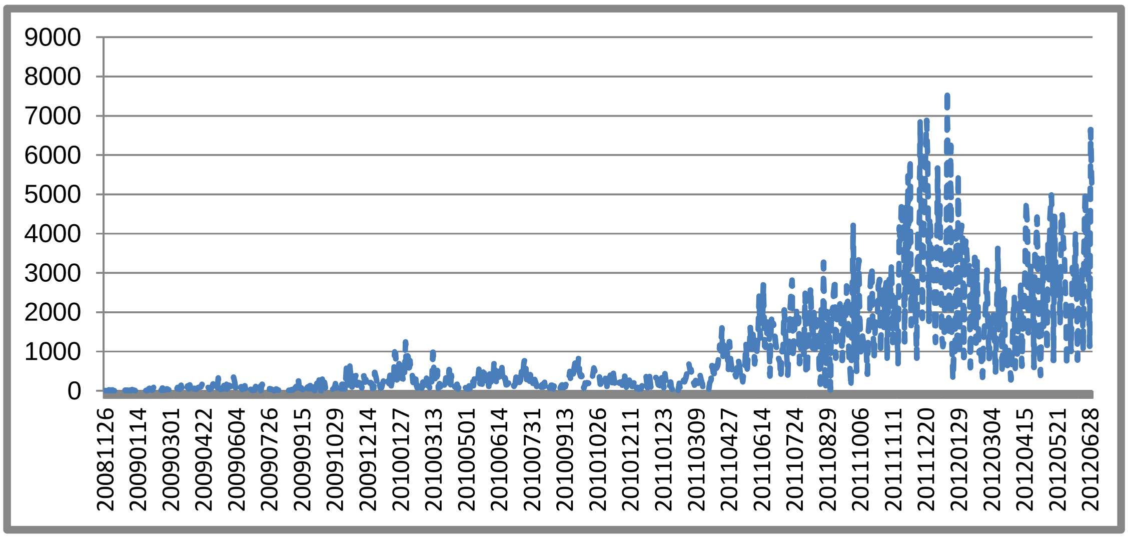
Compared to the historical volatility, range-based volatility estimators are claimed to be 5–14 times more efficient (e.g. Garman and Klass, 1980; Parkinson, 1980; Rogers and Satchell, 1991; Yang and Zhang, 2000). Moreover, Alizadeh, Brandt, and Diebod (2002), and Brandt and Diebold (2006) has shown that range-based volatility estimator appears robust to microstructure noise such as bid-ask spread and closing hours of market. Shu and Zhang (2006) get the similar result with Monte Carlo simulation by adding microstructure noise to the Monte Carlo simulation, Shu and Zhang (2006) also support that the finding of Alizadeh, Brandt, and Diebold (2002), that range estimators are fairly robust toward microstructure effects. Batten and Lucey (2007) shows that volatility in gold market is sensitive to fluctuation of other asset markets and suggests that risk managers should pay attention to other assets markets to make better diversification. Floros (2009) used different range-based models and find that simple measure of volatility overestimates the other estimators. Floros used five different S&P indices information and every time result was the same.

The rest of the paper is organized as follows: Section 2 introduces the futures market and gives a brief history of futures contracts in Iran. Section 3 provides the methodology and data information. Section 4 presents the main empirical results, while Section 5 concludes the paper and summarizes our findings.

2. Futures contracts in Iran

Futures Gold contract was first Futures contract that IME launch at 21 June 2008. Iran futures markets have seen several failure and success in last five years. We can say futures contracts are the only tradable derivatives in Iran and they play a great role in financial market.. Trading volume has grown rapidly in recent years (fig 1.) and makes them the most popular financial instrument in Iran financial market. Recent increase in systematic risk and absence of derivatives like options effects trading volume of futures in recent years.

Figure 1. Trading volume in Iran future market



Futures contract are new in Iran and some of them failed because of problem in structure of contract.

Table 1: History of Iran futures market

Contract	Description	Launch
AUOZMO87	Gold ounce	September 23, 2008
CRAZ87	Copper Rod 8 mm	September 15, 2008
GCDY87	Gold Coin	November 25, 2008
10GBAZ89	Gold Bullion 10 ounce	November 09, 2010

3. Methodology

Let H_t, L_t, C_t, O_t denote the high, low, closing and opening prices at day t, respectively. A simple measure of volatility is defined as the first logarithmic difference between the high and low prices (Alizadeh, Brandt and Diebold, 1999; Gallant, Hsu and Tauchen, 1999):

$$V_{s,t} = ln(H_t) - ln(L_t) \qquad \textbf{(1)}$$

Parkinson (1980) proposes a volatility measure assuming an underlying geometric Brownian motion with no drift for the prices:

$$V_{p,t} = \frac{ln(H_t) - ln(L_t)}{4ln(2)} \quad (2)$$

According to Chan and Lien (2003),$V_{p,t}$ could be as much as 8.5 times more efficient than log squared returns.

A further volatility measure is based on opening and closing prices. Garman and Klass (1980) suggest the following measure:

$$V_{GK,t} = \frac{1}{2}[ln\left(\frac{H_t}{L_t}\right)]^2 - [2ln2 - 1][[ln\left(\frac{C_t}{O_t}\right)]^2 \quad (3)$$

According to Chan and Lien (2003), both measures are unbiased when the sample data are continuously observed with $V_{GK,t}$, being more efficient than $V_{p,t}$. When the drift term is not zero, neither the Parkinson nor the Garman-Klass measures are efficient (Chan and Lien, 2003). Hence, an alternative measure with independent drift is required. Rogers and Satchell (1991) and Rogers, Satchell and Yoon (1994) propose a volatility measure which is subject to a downward bias problem:

$$V_{RS,t} = \left[ln\left(\frac{H_t}{O_t}\right)\right]\left[ln\left(\frac{H_t}{C_t}\right)\right] + \left[ln\left(\frac{L_t}{O_t}\right)\right]\left[ln\left(\frac{L_t}{C_t}\right)\right] \quad (4)$$

3.1 Required Data Input

The objective of this study is to report the volatility structure of gold coin, trading as a futures contract on the Iran Mercantile Exchange (IME). Iran Mercantile Exchange offers futures trading in a Gold coin contract that is deliverable (settled) against both cash and physical gold coin. The data employed in this study comprise 2386 daily observations on the Gold Coin Futures Contract in IME. This contract is available for the near month as well as any month falling within a 4-month period. Trading hours is Saturday through Tuesday: 10:00 AM to 6:00 PM and Thursday: 11:00 AM to 1:00 PM. This data covers the period 5 January 2009 till 12 May 2012. Closing, Open, High, and Low prices were obtained from IME web site.

Table 2: Descriptive Statistics (Prices)

GC Futures	**open**	**close**	**low**	**high**
Mean	4956749	4961910	4916668	5002066
Median	4546500	4550000	4514500	4573000
Maximum	9798000	9814000	9643000	9830000
Minimum	1970000	1970000	1962000	1970000
Std. Dev.	2094971	2098931	2061296	2131024
Skewness	0.33889	0.339142	0.330522	0.343212
Kurtosis	1.867553	1.867269	1.860625	1.866272
Jarque-Bera	173.1662	173.2979	172.5032	174.627
Probability	0	0	0	0
Sum	1.18E+10	1.18E+10	1.17E+10	1.19E+10
Sum Sq. Dev.	1.05E+16	1.05E+16	1.01E+16	1.08E+16
Observations	2386	2386	2386	2386

4. Empirical Results

In our daily range-based data highs and lows do not diverge over time (Appendix A). This is consisting with Cheng (2009), Floros (2009). The results from equations (1)-(4) are presented in Table 3. In all cases V_{ab} overestimatesV_p, V_{gk} andV_{rs}.

Table 3:

GC Futures	Vab	Vp	Vgk	Vrs	RV
Mean	0.014089	0.000138	0.000116	0.000112	5.95E-06
Median	0.0103	3.85E-05	3.33E-05	2.37E-05	8.50E-07
Maximum	0.146	0.007678	0.002418	0.003222	0.0011
Minimum	0	0	0	0	0
Std. Dev.	0.013569	0.000346	0.000232	0.00024	3.23E-05
Skewness	2.364051	10.68843	4.496753	4.693304	21.6368
Kurtosis	13.9629	185.8353	30.19012	34.75342	646.4891
Jarque-Bera	13018.67	3094894	74910.3	100136.8	37990175
Probability	0	0	0	0	0
Sum	30.88259	0.302691	0.253832	0.245383	0.013034
Sum Sq. Dev.	0.403381	0.000262	0.000118	0.000126	2.28E-06
Observations	2192	2192	2192	2192	2192

Volatility Estimates

Notes:

- Skewness is a measure of asymmetry of the distribution of the series around its mean.
- Kurtosis measures the peakedness or flatness of the distribution of the series.
- Jarque-Bera is a test statistic for testing whether the series is normally distributed.

4.1 Comparison between range-base volatility models

In order to examine the performance of range-base volatility models in volatility estimation, the result from four different models are compared with realized volatility as real observed volatility. RMSE, MSE, MAD and MAPE are used to observe the performance between those models.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(observed_t - estimated_t)^2}{n}}$$

$$MSE = \frac{\sum_{t=1}^{n}(observed_t - estimated_t)^2}{n}$$

$$MAPE = \sum_{t=1}^{n}\left|\frac{observed_t - estimated_t}{observed_t}\right| \times \frac{100}{n}$$

$$MAD = \sum_{t=1}^{n}\left|\frac{observed_t - estimated_t}{n}\right|$$

Tab. 4 gives the performance measure of different range-based models and depicts the error generated by different models.

Table 4: compare of Volatility models

Model	RMSE	MSE	MAPE	MAD
alizade	1.96E-02	3.84E-04	2.39E+06	1.41E-02
parkinson	3.71E-04	1.37E-07	1.70E+04	1.37E-04
garman -klass	2.58E-04	6.68E-08	1.52E+04	1.16E-04
rogers-satchell	2.65E-04	7.00E-08	1.47E+04	1.13E-04

The values of RMSE, MSE, given by Garman-Klass are smaller and value of MAD MAPE by rogers-satchell is smaller than other models.

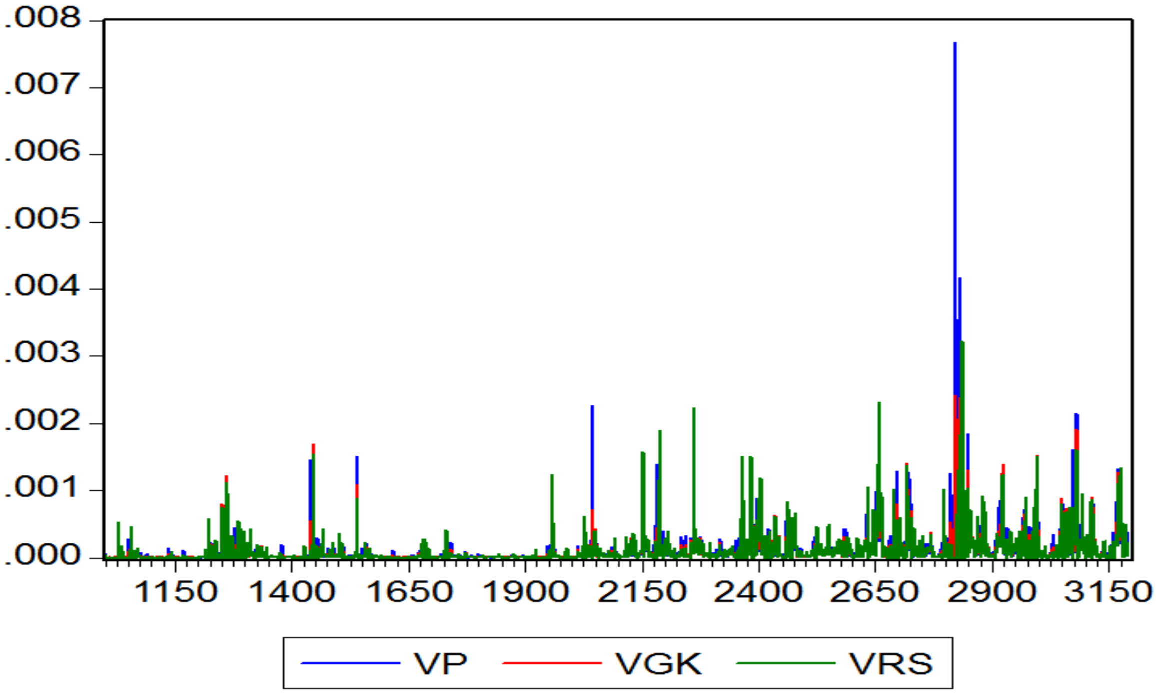


Figure 1. Parkinson, Garman and Klass, Rogers, Satchell volatility estimators

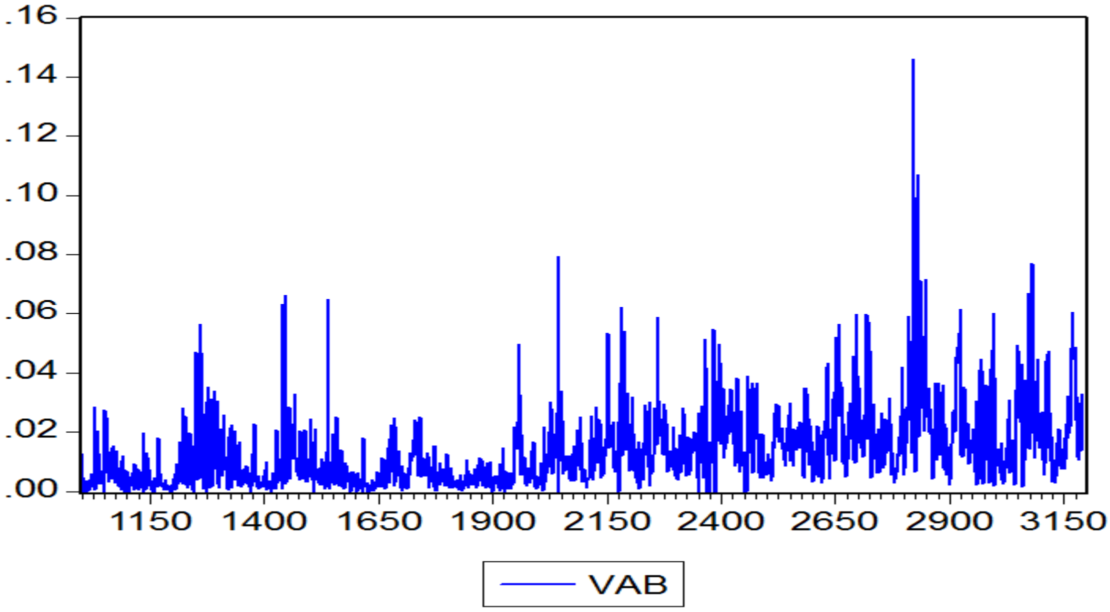


Figure 2. Alizadeh and Brandt volatility estimators

5. Conclusion

Volatility in financial markets has attracted growing attention by investors and researchers as it is a measurement of risk and unavoidable part of pricing of new financial instrument. The results reported in this paper show estimates of volatility in the Iran futures market. We model volatility using four models based on open, closing, high and low daily prices. Moreover, we consider daily data from Gold coin futures contract to test which measure dominates each other.

We find strong evidence that volatility can be characterized by Range-based models. In particular, we report that the prices have all financial characteristics: volatility clustering, platykurtosis and nonstationarity. Furthermore, daily range-based data highs and lows in our data do not diverge over time and are stationary.

We use four models to calculate daily volatility. The results show that Vs, a simple measure of volatility defined as the first logarithmic difference between the high and low prices, overestimates Vgk, Vp and Vrs. In order to compare accuracy of these models, we used realized volatility as proxy of actual daily volatility. Based on RMSE, MSE, model of Garman-Klass is more accurate and based on MAD MAPE model of rogers-satchell produces significantly more accurate daily returns volatility.

These findings are strongly recommended to risk managers and modelers dealing with the Iran financial market. Future research should examine the performance of range-based volatility estimator and parametric methods.

Appendix A: Result of Augmented Dickey-Fuller Test

Null Hypothesis: HIGH has a unit root

Prob.*	t-Statistic			
0.6213	-0.180308	Augmented Dickey-Fuller test statistic		
	-2.565932		1% level	Test critical values:

	-1.940957	5% level	
	-1.616610	10% level	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(HIGH)
Method: Least Squares
Date: 10/14/12 Time: 17:06
Sample (adjusted): 1001 3385
Included observations: 2385 after adjustments

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.8569	-0.180308	0.000669	-0.000121	HIGH(-1)

2467.925	Mean dependent var	-0.000179	R-squared
177669.8	S.D. dependent var	-0.000179	Adjusted R-squared
27.01384	Akaike info criterion	177685.8	S.E. of regression
27.01626	Schwarz criterion	7.53E+13	Sum squared resid
2.006317	Durbin-Watson stat	-32213.00	Log likelihood

Null Hypothesis: LOW has a unit root

Prob.*	t-Statistic		
0.6348	-0.141685	Augmented Dickey-Fuller test statistic	
	-2.565932	1% level	Test critical values:
	-1.940957	5% level	
	-1.616610	10% level	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOW)
Method: Least Squares
Date: 10/14/12 Time: 17:07
Sample (adjusted): 1001 3385
Included observations: 2385 after adjustments

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.8873	-0.141685	0.000648	-9.18E-05	LOW(-1)

2397.904	Mean dependent var	-0.000194	R-squared
168629.4	S.D. dependent var	-0.000194	Adjusted R-squared
26.90941	Akaike info criterion	168645.7	S.E. of regression
26.91183	Schwarz criterion	6.78E+13	Sum squared resid
1.968999	Durbin-Watson stat	-32088.47	Log likelihood

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