RESEARCH ARTICLE

Margin Setting to Short and Long Futures Contract Positions by Coherent Risk Measures

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Abstract

This study, using gold coins spot price returns, in the period from 2008to 2016, estimates and compares IME gold coin futures contracts short and long positions Initial margin by coherent risk measures, specially Expected Shortfall and spectral risk measures.GARCH, EGARCH and GJR GARCH used for volatility process modeling. Fore moles back-test, it applies Christophersonconditional coverage likelihood ratio (LRcc) test and Lopez and Blanco-Ihel loss functions, and Fore ES models Evaluations uses MAE and RMS Eloss functions. The paper finds that, GJRGARCH has outperformed the other models that support the asymmetric response of gold coins price to positive and negative shocks. The average margin estimated for short positions with all risk measures, is significantly larger than long positions that confirm asymmetric response of gold coins price to positive and negative shocks.

Keywords: *Blanco-Ihel Back test, EGARCH, Expected Shortfall, Exponential Spectral Risk Measure, Margin, Margin Setting.*

Introduction

Those measurement which are based upon integrated measures percentile of risk including expected shortfall and spectral risk measurements like symbolic spectral risk measurement and power spectral risk measurements are better than other ones.

Value at Risk process is always used for determining of margin setting. In spite of high efficiency of Value at Risk models for determining of margin setting and due to some non-efficiency such as subadditivity, it is impossible to include any risk integrated measurement. Since the Value at Risk is just one percentile, it has special applications but is not satisfying as a risk measurement. Therefore expected shortfall is better than Value at Risk along with subadditivity for risk measurement [1].

Of course, there are major weak points in expected shortfall models due to their applications including necessary benefits from levels of significance and also lack of attention to the risk aversion nature. Therefore most researchers pay nice attention to applying of risk spectral measurement. The most important form of them is Exponential and Power weighting functions. These measurements provide a final risk digit with regard to risk aversion level and free from any needs to determine confidential level.

Since the major part of all these models is based upon estimations percentile, if there are dissimilar variance in distribution of parts, any lack of attention to this matter may cause incorrect estimation of models. Therefore, we used general self-regression models of GARCH for modeling of fluctuations especially with lack of symmetric data [2].

Basic assets play the important role in extracted interactions of price fluctuations and also determining of margin setting in future contracts. It is the major tool of risk management in interaction room.

The mentioned organization is able to reduce any margin setting of parties of contracts and also risk of default of customers by obtaining margin setting and daily settlement of future contracts [3]. Although high levels of margin setting may keep interaction room and agents against any risk default, but the margin settings are always considered as an interaction costs for investors and parties of future contracts. Therefore it is really serious

for interaction rooms to make correct calculations of margin setting [4].

This paper intends to compare various models of GARCH family for calculation of margin setting in future contracts of gold coin at Iranian Stock Exchange and by focusing on risk integrated measures including exponential & power weighting functions. Finally we have compared separately all functions of these models in estimation of margin setting in buying / selling positions.

Theoretical literature & Research History

If we show the margin setting, price changes and probable distribution function of price changes respectively by ML and F(x), then we may calculate any probable insufficiency of margin setting in a day by the use of a dangerous value model as follows [5]:

$$p = \text{prob}(\Delta p > ML) = F(ML) \qquad (1)$$

Although any attitudes based upon value at Risk Approach are suitable models for estimation of margin setting, but there is a weak point here which is higher losses than the same. This is exactly the same factor which is really important for extracted contracts interaction room. This is because in case of any fluctuations in prices rather than Value at Risk, this case is really serious from viewpoint of risk management.

Whether the mentioned amounts in current guarantee accounts which are sometimes more than specified rates by Stock Exchange could cover any losses resulted from these changes or not. This criteria that means α percent average is the worst loss and could be calculated by the following formulation [6]:

$$ES_\alpha = \frac{1}{\alpha} \int_0^a VaR\,(x)dx \qquad (2)$$

Regarding some application weak points with which most expected shortfall models are facing, it is useful to apply risk spectral measurement. Risk measurement may not only calculate considered risk without any needs to level of significance but also will consider people risk aversion level in weighing function. This measure is the weighted average of efficiency distribution percentile. If we consider M_φ as the risk measurement, we will have:

$$M_\varphi = \int_0^1 \emptyset(p)F^{-1}(x)dp \qquad (3)$$

Where:

$\emptyset(p)$ is the weighted function which should be determined and named as risk spectral function. As a result, ES and VaR are special cases out of the above-mentioned relationship. Weighting functions should bear three conditions of non-negative, normal and weakly increasing.

The first two conditions which are always available mean that all weights should be non-negative and their total amount is equal to 1. It is also true for Value at Risk and expected shortfall. But the third condition illustrates risk aversion. This means that special weights for higher weights should be higher and/or equal with smaller losses.

Since all these weights are related to risk aversion of people in spectral risk measures, therefore they are increasing weights. The weight rate of weights depends upon people risk aversion. Therefore we should determine risk aversion of people in order to extract any weighting function in a risk spectral measurement. The most famous functions are *Exponential weighting Function* and *Power Weighting Function.*

Experimental History

Up to now there are lots of studies about various dimensions of future contracts. Regarding the importance of margin setting in structure of future interactions and their mutual relationship with most parameters of market, a considerable share of these studies are about optimization of margin setting in future contracts.

Hessieh could explain the importance of conditional non-harmonized model making in margin setting for the first time. He proposed that Conditional Probable Distribution Function could be useful in determining of margin setting [7].

By applying GARCH model, Cutter considered a conditional process for distribution of future prices (in order to evaluate any relevant issues with activity characteristics of future price fluctuations)[8]. Knot &Pullengi have also estimated guaranteed amount of future contracts by the use of variance dissimilar

Models [9]. By the use of Garch model and considering inter-activation of future contracts, Cutter and Langin calculated Fotsi Index and margin setting of future contracts [10]. Doud et al. considered spectral risk index and further advantages and disadvantages as well [11].

By the use of Risk Integrated measurements, Cutter and Doud evaluated the margin setting in any contracts for buying/selling contracts [12]. Jayans Varma evaluated in their research any situation of extracted stock exchanges in financial crisis of 2008.

They concluded that extracted stock exchange need to use Risk Integrated Measurement including expected shortfall for determining of margin setting [13]. In order to calculate required margin setting for outer-stock exchange extractions which are settled in stock exchange, Heller &Vaous used Risk Integrated measurements and concluded that the best solution for reducing of required guaranteed amount is to combine extracted interactions rooms out of the stock exchange [14].

In another research, the expected shortfall models have been calibrated with Value at Risk and other measurements for calculation of required guaranteed amount plus interest rate and future contracts. Then the result has been applied in historical margin setting of stock exchange [15].

Although there are not some considerable studies in this field in Iran, but there are only two specific researches in this spectral. In a research based upon statistics of future contracts of gold coin at Iranian Stock Exchange and by the use of multimodal GARCH model, Fallah could studied any effects of changing the margin setting on price, price fluctuations and volume of transactions.

According to the results, there is a negative relationship between increase of margin setting and price of future contracts and volume of transactions and also a positive relationship between increase f margin setting and price fluctuations of future contracts [16]. In another research, Karimi has calculated the margin setting of future contracts by the use of conditional value theory [17].

The present study has estimated required margin setting for buying/selling of gold coin future contracts in Stock Exchange by the use of Value at Risk and integrated risk measures such as expected shortfall and symbolic risk spectral based upon GARCH family models and traditional value models.

Then we have compared them accordingly. Regarding all applied models in this study, followings are relevant hypotheses of this research:

First Hypothesis

Value at Risk model and expected shortfall of GJR has better functions in any level of significance than GARCH model.

Second Hypothesis

Value at Risk model and symbolic GARCH expected shortfall has better functions in any level of significance than GARCH model.

Third Hypothesis

The average of estimated margin setting by all measures for selling positions is significantly higher than buying ones.

Research Methodology

This study is promotional-applicable from viewpoint of the goal and also a back-test study based upon data analysis as well. We have used maximum likelihood method for estimating of GARCH parameters. In addition, we used Simpson s Rule and p division into 10,000 pieces in order to calculate of risk integrated measure. Also we used Comp Econ calculations in MATLAB software. In order to measure acceptable rate of models from statistical viewpoint, we used Kupiec Backtest and Christffersen Conditional Coverage Test and also Lopez Loss Function and Blanco-Ihel for classification of expected shortfall models and also applied both loss functions including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as well[18]. We used MATLAB and SPSS software for estimation of parameters and also margin settings and test performances.

Data Collection Tools

Data Collection in this study was made by documentary observation method. All necessary data were collected from various notes and documents of Data Bases of Gold & Jewelries Union. Research sample incudes

cash prices of gold coin from 2008 up to 2015; therefore the local scope of this research is cash prices of gold coin in Iranian Market. Regarding the startup of future contracts at Iranian Stock Exchange from 2008, the time scope of this study is within 2008 up to 2015. Meanwhile the only applicable and active contract in Stock Exchange is based upon BaharAzadi Coin which has been started on 26.Nov.2008 up to now. It has included about 1991 interactional days. As a result, we used totally 1990 cash price output for gold coin. Furthermore, price logarithm differential has been used as entrance data in all estimations.

Research Models

It is necessary to have fluctuations modeling in order to calculate any value at risk and expected shortfall and risk measures. All fluctuations are modeled in this research by various models such as GARCH (1, 1), EGARCH (1, 1) and GJRGARCH (1, 1) as follows:

Conditional Variance Dissimilar Model

Following is the Conditional Variance Model

$$ln\sigma_t^2 = k + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i ln\sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma i \left(\frac{|\epsilon_{t-i}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right)$$

(5)

Parameter γ could measure any dissimilarity effects of shocks. If it is not zero, then it is a sign of dissimilar effect of shocks on fluctuations. If it is positive, it is a sign that positive shocks have more effects on conditional fluctuations than negative ones.

$$\sigma_t^2 = k + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i o_{t-j}^2 + \sum_{i=1}^{p} \gamma_i I_{t-1} \epsilon_{t-i}^2$$

(6)

Coherent Risk Measures

The following formula is applied for calculation of Value at Risks after model making of fluctuations.

$$VAR_{t+1,p} = \mu_{t+1} + o_{t+1}\phi^{-1}(p)$$

(7)

Where:
$\phi^{-1}(p)=$ the standard normal distribution percentile
$\mu_{t+1} \& o_{t+1} =$ are estimations of average and standard violation within t+1 which are calculated out of information

$$\sigma_t^2 = k + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i o_{t-j}^2$$

(4)

Where GARCH (1, 1) k illustrates the fixed amount and α_1 illustrates the regression coefficient of previous fluctuations and β_1 illustrates the regression coefficient of final period. All parameters of this model are positive with relevant condition of:

$\alpha + \beta < 1.$

Exponential Conditional Variance Dissimilar Model (EGARCH)

By the use of this model, it is possible to make a model for leverage effects. According to the meanings of leverage effects by Black & French et al., all changes in price of an asset has a negative coefficient with the fluctuations as well[19]. There is not any limitation on coefficient sign in this model; therefore it is not necessary to make any limitations for non-negative coefficients. Secondly, in above-mentioned model, there are some positive and negative shocks for non-fixed condition as well. EGARCH (1, 1) model which is applied in financial literature is as follows:

Conditional Variance Dissimilar Model of GJR

This method could make a model for non-comparable situation in GARCH process and has been presented by Glasten, Janathan and Ronkel. In case of more shocks in negative fluctuations, then this model is suitable for model making of fluctuations [20]

Expected shortfall based upon mentioned model is also calculated as follows [21]:

$$ES_\alpha = \mu_t + \frac{f(x_\alpha)}{p}\sigma_t$$

(8)

Where:
$f(x_\alpha)$
$= Density\ of\ probable\ normal\ distribution\ for\ \alpha^{th} percentile$

In order to calculate exponential & power weighting functions, we should define suitable weighing functions as well. The most famous function is exponential weighting function and power weighting one. Following

is the calculation method of Exponential weighting function:

$$\phi(p) = \frac{ke^{-k(1-p)}}{1-e^{-k}} \qquad (9)$$

$$M\varphi(0,1) = E\,SRM = \int_{0}^{1}\phi(p)q_p dp = \frac{k}{1-e^{-k}}\int_{0}^{1}e^{-k(1-p)}z_p dp \qquad (10)$$

Regarding the above-mentioned equation, following is the calculation method of exponential risk spectral measure for normal distribution with average μ and standard violation of σ: $\qquad (11)$

$$M\ (\mu,\sigma) = E\,SRM = u_t + \sigma_t\,E\,SRM(0,1)$$

$$M\varphi(0,1) = P\,SRM = \int_{0}^{1}\phi(p)q_p dp = \int_{0}^{1}\gamma(1-p)^{\gamma-1}z_p dp \qquad (12)$$

Where:

γ= Relative risk aversion coefficient

$0(0< \gamma < 1)$

Regarding the above-mentioned equation, following is the calculation method of power risk spectral measure for normal distribution with average μ and standard violation of σ:

$$M\ (\mu,\sigma) = P\,SRM = u_t + \sigma_t\,P\,SRM(0,1) \qquad (13)$$

Verification of Models

For verification of models, we used a 2-step process. We applied Kupiec non-conditional coverage tests and Christopher son conditional coverage in first step. Then we used loss functions including Lopez second function of loss and Blancko-Ihel Loss function for comparing of models in second step.

We are searching for accuracy tests of models from statistical viewpoint in first step. In case of higher and real data (price changes) than estimated amount by model, then it is considered as a failed accident. In first step we are searching to find an answer to this question that whether it is possible to have probable equation in each test (it means model level of significance) according to the number of fails to total estimated amounts. As a result, accuracy of a value at risk model is tested from statistical viewpoint. If is not rejected, then it is accepted accordingly. Needless to state that all models are

Where absolute risk aversion coefficient is greater than zero and p is probable occurrence of each percentile. Therefore the following formulation illustrates Exponential Spectral Risk Measure.

If we use Power weighting function instead of exponential weighting function, then power spectral risk measure is as follows for standard normal distribution:

approved in this step from statistical viewpoint. The major remained problem is selecting a suitable model from among approved ones. Therefore, we will have classification of models by suitable loss functions in second step. For better classification of models, we should specify the loss function from among different loss functions as well. The second Lopez Loss Function is one of the most applicable loss functions which is defined as follows:

$$C_t\begin{cases}1+(L_t-VaR_t)^2 & if L_t > VaR_t \\ 0 & if L_t \le VaR_t\end{cases} \qquad (14)$$

This formulation makes it possible to calculate current losses in a sequence and provides more amounts to a model with higher sequence losses. Therefore in case of higher average of sequence losses will have weaker functions in return.

$$QPS = \frac{2}{T}\sum C_t \qquad (15)$$

One of the defects of this model is lack of specific meaning for square of higher losses than VaR. It will make us so much confused. In order to solve this problem, Blanckko – Ihel have proposed the following loss function:

$$C_t\begin{cases}(L_t-VaR_t)/VaR_t & if L_t > VaR_t \\ 0 & if L_t \le VaR_t\end{cases} \qquad (16)$$

Intuition of this loss function is so much easy and will ensure us about higher losses than

C_t. Meanwhile; we have comparison criteria as follows:

$$P_t = \frac{ES_t - VaR_t}{VaR_t} \qquad 17)$$

Grade function for Blancko-Ihel model is as follows:

$$QPS = \frac{2}{T} \sum (C_t - P_t)^2 \qquad (18)$$

The obtained results illustrate the loss function of models. Higher amount of loss function in a model means weak operation of it [1]. In addition, for classification of expected shortfall models we will use Mistakes Absolute Estimated Loss function and also RMSE for selection the best model of expected shortfall.

Lower amount of these mistakes will naturally have better functions in return [18].

Descriptive statistics of data illustrates a wider sequence of normal distribution and skewed to the right for data. Jarque-Bera test has also similar results as well. As it is obvious in table 1, test statistics is greater than critical amount in error level of %5. Therefore we seriously reject normal output of prices. As it is obvious in descriptive statistics of data, the real reason is mainly tension of data more than ever. Regarding any presence of unique root, Dickey-Fuller test illustrates that any changes of prices are fixed with the intercept.

$$RMSE = \sqrt{\frac{2}{T} \sum (C_t - ES_t)^2} \qquad (19)$$

$$MAE = \frac{2}{T} \sum |C_t - ES_t| \qquad (20)$$

Table 1: Descriptive statistics of data & results of data normality test

	No. of data	Elongation	Skewness	Standard violation	Mean	Critical amount of test at error level of %5	Test statistics	P-value
Differential of price logarithms	1990	17.83	0.37	0.01585	0.00095	5.96	16899	0.001

Estimation of Garch Models Parameters

Firstly we made a GARCH model (1, 1) for all GARCH models in order to evaluate any self-regression and ARCH effect. Table 2 illustrates the results of estimations. We used Ljung-Box test for all zero assumption models. It means rejection of any lack of presence of any self-regression for disorder parts. Therefore all these data have a self-regression. In addition, we used ARCH LM test for evaluation of any ARCH effects. ARCH test will seriously reject any presence of variance similarity in mistake parts.

Therefore it is acceptable to use GARCH models. The results of Ljung-Box & ARCH tests for square of standard parts after estimation of model parameters may approve the assumption of no more efficiency and variance similarity in different stops.

Table 2: The results of garch model parameters estimation

Parameters	GARCH	Exponential GARCH	GJR GARCH
K	0.0	-0.685	0.0
Standard violation	0.0	0.099	0.0
α	0.355	0.493	0.255
Standard violation	0.0270	0.031	0.03
β	0.644	0.916	0.66
Standard violation	0.024	0.011	0.023
γ		-0.097	0.168
Standard violation		0.017	0.04

Determining of Data Framework for Estimation of Margin Setting

In order to benefit from data and estimate margin setting by the relevant measures, firstly we should determine mobile framework of data. For this purpose, we should classify all data into two groups of inter-sample and outer-sample as well. For performing of after-test experiments and comparing of method with each other, we

used from data 1 to 990 and estimated under-risk vale by different methods for 991st period with different level of significances. Then we used data 2 to 991st and relevant estimation of 992nd period and so on up to final estimation of 1990[21]. In order to calculate margin setting for buying/selling positions separately from higher and equal to zero data and smaller and equal to zero data, we classified all processed buying/selling positions including 1134 and 1066 into two groups of inter-sample and outer-sample. Inter-sample data are applied for selling position of 634 data and buying position of 566 data. We made 500 estimations in each case. All estimations in this research will be performed with 3 levels of significances of 95, 99.9 and 99 percent.

Table 3: The results of estimation margin settings for buying/selling positions with ES &var

	Level of significance	Value at Risk (VaR)			Expected shortfall (ES)		
		Total	Buying	Selling	Total	Buying	Selling
GARCH	%95	2.97	3.1742	2.8274	3.53	3.7600	3.3325
	%99	3.88	4.1297	3.6512	4.35	4.6048	4.0608
	%99.90	4.94	5.2006	4.5745	5.34	5.5888	4.9092
Symbolic GARCH	%95	3.01	2.2814	1.8560	3.57	2.8471	2.3037
	%99	3.92	3.2041	2.5862	4.38	3.6628	2.9493
	%99.90	4.97	4.2383	3.4047	5.36	4.6131	3.7014
GJR GARCH	%95	2.97	3.1617	2.8242	3.53	3.7470	3.3262
	%99	3.88	4.1163	3.6429	4.34	4.5910	4.0500
	%99.90	4.93	5.1864	4.5606	5.32	5.5742	4.8932

Tables 3 & 4 illustrate the estimation results of margin setting which are calculated by average margin settings for any selling & buying positions by symbolic & power spectral risk measurements and Value at Risk and expected shortfall.

Results

Tables 5 & 6 illustrate the results of back-tests of models. According to the results, it is understood that:

The percentage of all models in Christopher son conditional coverage test is approved at level of significance of %95 and %99. Meanwhile none of the models were approved at level of significance of %99.9. Since the conditional coverage test is the consequent of both LR_{UC} and LR_{ind} tests, it is more important. But as it is obvious in table 6, there are some different results in both mentioned tests.

We classified value at risk models in accordance with Blancko –Ihel loss function and also Lopez 2nd loss function from which Blancko-Ihelloss function is more suitable as well. In addition, we made necessary classification just for any models which have not yet rejected in first step.

No more models have been approved at level of significance of %99.9. GJRGARCH Model had the best functions among value at-risk models and expected shortfall at level of significances of %99 and %95. Therefore with regard to MAE and Blancko-Ihel criteria, we could approve the first hypothesis but it is not the same for second hypothesis.

Table 5: The results of margin setting at various level of significances & back-tests of models

	Level of significance	VaR	Breakage rate	LR_{cc}	LR_{ind}	LR_{uc}
GARCH	%95	2.97	0.037	4.04	0.14	3.89
	%99	3.88	0.014	3.06	1.62	1.43
	%99.90	4.94	0.007	19.13	3.85	15.27
Exponential GARCH	%95	3.01	0.038	3.53	0.24	3.29
	%99	3.92	0.014	7.90	6.46	1.44
	%99.90	4.97	0.009	33.49	9.88	23.61
GJR GARCH	%95	2.97	0.038	3.48	0.19	3.29
	%99	3.88	0.019	7.20	0.73	6.47
	%99.90	4.93	0.006	15.93	4.40	11.53

Table 6: The results of comparison of models at various level of significances with lopez, blancko –ihel, mae and rmse functions

		Expected shortfall					value at risk				
		95	rank	99	rank	99.9		95	rank	99	rank	99.9
GARCH	ES	3.53		4.35		5.34	VaR	2.97		3.88		4.94
	Standard deviation	1.98		2.45		3.00	Standard deviation	1.66		2.18		2.78

	RMSE	0.003	(1)	0.0049	(3)	0.0075	Lopez	0.074	(1)	0.0280	(1)	0.0140
	MAE	0.0686	(2)	0.0861	(2)	0.1062	Blancko-Ihel	0.1112	(2)	0.0479	(2)	0.0215
Exponential GARCH	ES	3.57		4.38		5.36	VaR	3.01		3.92		4.97
	Standard deviation	1.75		2.16		2.65	Standard deviation	1.48		1.93		2.45
	RMSE	0.003	(1)	0.0047	(1)	0.0071	Lopez	0.0760	(2)	0.0280	(1)	0.0180
	MAE	0.0695	(3)	0.0869	(3)	0.1067	Blancko-Ihel	0.1267	(3)	0.0546	(3)	0.0242
GJR GARCH	ES	3.53		4.34		5.32	VaR	2.97		3.88		4.93
	Standard deviation	1.98		2.44		2.99	Standard deviation	1.66		2.18		2.77
	RMSE	0.003	(1)	0.0048	(2)	0.0074	Lopez	0.076	(2)	0.0380	(2)	0.0120
	MAE	0.0684	(1)	0.0854	(1)	0.1059	Blancko-Ihel	0.1103	(1)	0.0473	(1)	0.0211

Table 7 illustrates the results of comparison tests for buying/selling positions for spectral risk measures. The results illustrate that estimated margin setting for selling positions are significantly greater than buying ones along with all GARCH models. Furthermore, the margin setting of sale is greater than total margin setting in most models except in exponential GARCH model. There were similar results for both tests of value at-risk measures and expected shortfall. Therefore the third hypothesis is approved accordingly.

Table 7: Average comparisons test of estimated results out of spectral risk measures for buying/selling positions

Absolute & estimated risk aversion coefficients (K, γ)		Comparing with all positions			Comparing with buying positions		
		GARCH	Exponential GARCH	GJR GARCH	GARCH	Exponential GARCH	GJR GARCH
Exponential measure	1	0.00782*	-0.00101*	0.00752*	0.00083*	0.00040*	0.00065*
	5	0.00717*	-0.00197*	0.00695*	0.00238*	0.00266*	0.00225*
	25	0.00646*	-0.00301*	0.00633*	0.00407*	0.00513*	0.00399*
	100	0.00601*	-0.00368*	0.00594*	0.00513*	0.00668*	0.00509*
	500	0.00562*	-0.00424*	0.00561*	0.00604*	0.00802*	0.00603*
Power measure	0.1	0.00648*	-0.00299*	0.00635*	0.00401*	0.00506*	0.00394*
	0.5	-0.00152*	0.00722*	0.00748*	0.00164*	0.00159*	0.00149*
	0.9	0.00797*	-0.00079*	0.00765*	0.00047*	0.00012	0.00029*

Conclusion

Regarding the importance of margin setting in future contracts as an important function and in fact better chances for the holders, the calculation method of margin setting by interaction room is always so much important. Upon estimation of expected margin setting in future contracts and by the use of value at-risk models and expected GARCH shortfall based upon Normal disorders and T-student, exponential GARCH and GJR GARCH, we find out different results in this study. Therefore upon applying of back-tests we may find out a general conclusion.

All models had no more suitable functions at high levels of significance. Furthermore, GJRGARCH model had better functions than other models. This is a sign of dissimilar reactions of gold coin price fluctuations against negative/positive shocks. In addition, all estimated amounts for margin setting are significantly greater than sales and by the use of all measures. This is a sign of dissimilar reaction of price fluctuations to negative/positive shocks.

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