Estimation Of Hedging Effectiveness Of SGARCH Model

Anuja Gupta, Manoj Jha, Namita Srivastava

Abstract: The main aim of this article is to assess the hedging performance of a new class of GARCH model called SGARCH model and a statistical technique called wild bootstrap method. For establishing the model, hedge ratios and corresponding hedged portfolios are constructed. Also unhedged and hedged portfolios are compared using the parameters hedge ratio, hedging effectiveness, variance and semi-variance. The data set consists of daily spot and future price of the CNXNIFTY50 index for the period Jan 2006-Dec 2015. Wild bootstrap has two components viz. residual and paired resampling methods. These are percentile based methods and provide a range of hedging strategies which are more informative and safer than ordinary least square method. With the help of SGARCH model, time varying hedge ratios are estimated. This model involves less number of parameters which made it easy to understand and compute. For comparing the hedging effectiveness, $R^2$ or the coefficient of determination is used. Throughout this study, it was found that hedging done through SGARCH model provide better results than the wild bootstrap method. The findings of this analysis may prove to be highly valuable for investors trying to reduce the spot portfolio risk for longer time horizon.

Index Terms: time series, heteroscedasticity, multivariate GARCH models, wild bootstrap method, hedging;

1. INTRODUCTION

EVERY investor needs maximum profit and for this he makes his investment in such a way so as to protect himself from likely losses. He adopts different measures of risk to achieve this target. Modern techniques of market risk management are based primarily on models of stochastic processes [1]. The desired model should be selected on the basis of fulfillment of all properties of a time series. Risk reduction is the primary function of futures market. Various measures and models are given in the literature to reduce risk. Hedging is also a risk minimizing strategy similar to an insurance policy. Hedging is recently being used by investors and traders for trading in equities, bonds, currencies, and other financial securities. Due to strong relationship between spot and future market, a new investment is formed by combining the investments of both these markets to minimize the risk of spot market [2]. Three types of hedging theories are prevalent in literature viz. conventional, Working and mean-variance hedging theory. According to conventional or naive hedging theory, an investor is not only risk averse but also averse to price movements in futures market and that cash and future market are perfectly correlated. This theory was criticized as it failed to explain the impact of basis risk [3]. Working’s (1953) theory assumed that the main objective of hedger is to maximize the returns and without minimizing the risk [4]. This theory was also criticized because an investor cannot always maximize his profit at any level of risk. Johnson (1960) and Stein (1961) proposed portfolio hedging theory or the mean-variance hedging theory which assumed that the main purpose of hedger is neither minimization of risk nor maximization of returns, but to optimize risk-return simultaneously in the portfolio [4]. Ederington (1979) employed the work of Johnson and Stein in estimating Minimum Variance Hedge Ratio. He also introduced the concept of hedging effectiveness [3, 5]. The work done by Ederington has got huge support in literature. The portfolio hedging theory helps in estimating both the static and dynamic hedge ratios. Various studies in the past have used Ordinary Least Square (OLS) method for estimating hedge ratios. But it was criticized due to its biased nature and autocorrelations in the OLS residuals. Also it provides no information about the inherent risks associated. To overcome this difficulty various other alternatives and time-varying GARCH models have been provided in the literature. SGARCH is also one of them. The simplified multivariate GARCH model (SGARCH) is a time series conditional heteroscedasticity model which is used mainly for hedging [6]. This research aims at finding hedge ratios and related hedging effectiveness with SGARCH model and the percentile based wild bootstrap method which is non-parametric, interval estimation based method [7-9]. The research is conducted by examining one of the main index of NSE viz. NIFTY50. This study uses near month future contracts from their respective start date until 31 Dec 2015. Monthly average of the daily data is chosen as hedging horizon. SGARCH model is known to remove the computational problems which other GARCH models have. Similarly wild bootstrap method provides a range of hedging strategies within 95% confidence interval. It can remove the problems with the single point estimation methods. This research will offer substantial input to the literature and will assist researchers and financial analysts in financial decision-making. This research helps to conduct a better informed hedging and more detailed risk analysis. The findings of the research shed new light on selection of an appropriate hedging strategy with dynamic hedge ratios. Rest of the paper is organized as follows. Section 2 illustrates the literature review. Section 3 describes the research methodology and background to the analysis. Section 4 contains numerical illustration with data description, results and comparative analysis. Section 5 concludes the paper.

2 LITERATURE REVIEW

SGARCH is a multivariate GARCH model given by Harris, Stoja and Tucker in the year 2007. This model is easy to understand and compute than other GARCH models as it involves less number of parameters to estimate. Harris and Shen [10] estimated optimal hedge ratio (OHR). He employed rolling window approach and the exponential weighted moving average approach (EWMA). Comparison is done using standard rolling window and EWMA estimators. Turvey and Nayak [11] estimated OHR using semi-variance. This study provides an algorithm to solve for the minimum semi-variance hedge. Harris et. al., [6] estimated minimum variance hedge ratio using SGARCH model. Comparison is done using Diagonal vech, Constant Correlation, BEKK and Dynamic Conditional Correlation model. Bhaduri et. al., [3] evaluated OHR by analyzing OLS, VAR, VECM and DVEC-GARCH models. A comparison between hedged and unhedged portfolio is done using the criterion mean and variance under
different hedging horizons. Zhou and Wu [2] estimated and forecasted OHR using Naive, OLS and SGARCH hedging strategy. Iqbal [12] presented the robust M-estimation of multivariate GARCH models using SGARCH model. Lien [13] compared the hedging effectiveness of conventional and time-varying conditional hedge ratios. It was concluded that the conventional hedge ratios are better in large sample cases. Nguyen et. al.[14] estimated minimum variance hedge ratio using wild bootstrap percentile method and compared it with DCC GARCH model. Singh [4]suggested an optimal hedge ratio by analysing NIFTY, BANKNIFTY, and NIFTYIT using OLS, GARCH, EGARCH, TARCH, VAR, and VECM models. Gupta and Kaur [15] estimated hedging effectiveness of NIFTY50 index futures. This study also employed 17 composite stock futures of NIFTY50 index. The models used in the study were Naive, Ederington's OLS, ARMA-OLS, VAR, VECM, GARCH, EGARCH and TAR.CH. From the literature review it is observed that most of the researches were confined to foreign stock markets index and very few evidences were available for Indian stock market index. In this research SGARCH model is applied to find the Minimum Variance Hedge Ratio (MVHR) and hedging effectiveness for Indian stock market index and compared it with wild bootstrap method of Efron (1979) [8].

3 METHODOLOGY
This study estimates hedge ratios and hedging effectiveness using SGARCH model and wild bootstrap method. In this section, the basic terminology of hedging, models and methods used are discussed.

3.1 Hedge ratio
It compares the value of hedged position with the size of entire position itself [16]. The value of hedge ratio should be as low as possible. Higher hedge ratios require more future contracts which in turn demand higher investment. The traditional method of obtaining MVHR is the OLS method [3] given by

\[ r_{st} = C + \beta r_{ft} + \epsilon \]  

(1)

This minimum variance hedge ratio minimizes the variance of hedged portfolio return. Hedged portfolio returns are given by [3]

\[ r_h = r_{st} - \beta r_{ft} \]  

(2)

Where \( r_h \) is vector of \( h \) is the hedged portfolio returns \( r_{st} \) is a vector of spot portfolio returns given by

\[ r_{st} = \ln \frac{s_t}{s_{t-1}} \]

\( r_{ft} = \ln \frac{f_t}{f_{t-1}} \]  

(3)

\[ C = \text{a constant} \]

\[ \epsilon = \text{residual term} \]

\[ s_t = \text{spot price at time } t \]

\[ f_t = \text{future price at time } t \]

\[ \beta = \text{hedge ratio given by} \]

\[ \beta = \frac{\text{cov}(r_{st}, r_{ft})}{\text{var}(r_{ft})} \]  

(5)

Where numerator is the covariance between the returns of spot and future portfolio. Denominator is the variance of future portfolio returns [17]. Each vector of the above returns has a length of \( n \), which denotes the sample size. Hedging through future contracts protects initial investment from adverse price changes with the number of future contracts determined by the hedge ratio. The conventional approach to this task is to use the estimate of \( \beta \) based on the regression of the form given by Eq (1). The OLS estimator for \( \beta \) in Eq (1) is expressed as

\[ \hat{\beta} = (r_{ft} r_{ft})^{-1} r_{ft}^T r_{st} \]  

(6)

Where the superscript \( T \) refers to the transpose of the corresponding vector.

3.2 Hedging effectiveness
To assess the effectiveness of a hedging strategy, hedging effectiveness is used. It is defined as the extent to which hedging an instrument actually reduces risk. It is the percentage reduction between the variance of hedged and unhedged portfolio. It is given by [4]

\[ \text{HE} = \frac{\text{Var}(U) - \text{Var}(H)}{\text{Var}(U)} \]  

(7)

Where \( \text{Var}(U) = \sigma^2_{\epsilon} \) is the variance of the returns of unhedged portfolio \( \text{Var}(H) = \text{Var}(r_{st}) + \beta^2 \text{Var}(r_{ft}) - 2\beta \text{cov}(r_{st}, r_{ft}) \) is the variance of hedged portfolio returns [4]. The higher the value of hedging effectiveness, the better is the hedging and vice versa.

3.3 Wild bootstrap method
Bootstrap (Efron 1979) is a new method to find optimal hedge ratio. It is a non-parametric hedging strategy based on repeated resampling of the data under study. This method consists of (a) residual resampling which assumes that \( r_{ft} \) in Eq(1) is exogenous variable and uncorrelated with error term and (b) paired resampling which assumes that \( r_{ft} \) in Eq(1) is random. The wild bootstrap based on residual resampling is as follows:

1. Find the value of hedge ratio \( \beta \) from Eq (6)
2. Draw a bootstrap sample \( (r_{st}^{*}, r_{ft}^{*}) \) based on \( \hat{\beta} \) for each ith observation from 1 to \( n \) using the identity

\[ r_{st}^{*} = \hat{\beta} r_{ft}^{*} + t_{i-1}^{*} \]  

(9)

Where \( t_i \) is an independent random variable with zero mean and variance one

\[ \hat{\epsilon}^{*}_{i-1} = \frac{\text{transformed residual from the regression (1),}}{} \]

robust to heteroscedasticity.
3. Again compute the new value of the hedge ratio \( \hat{\beta} \) with the bootstrap sample \( (r_{st}^{*}, r_{ft}^{*}) \) for \( i = 1, \ldots, n \) following the regression (1).
4. Form a bootstrap distribution for \( \hat{\beta} \) by repeating steps 2 and 3.
5. Construct (1- \( \alpha \)) 100% confidence interval with the lower and upper limits representing the 0.5\( \alpha \) percentile and (1– 0.5\( \alpha \)) percentile respectively of the distribution formed in step 4. The percentiles within the confidence interval can
be estimated in a similar way. The number of bootstrap iterations is set at 1000.

6. In paired resampling the whole procedure is repeated except step 2 and 3. Resampling and estimations are conducted as (r_{st}^{*,r}, r_{st}^{*,f}) = (τ_i r_{st}^{*,r}, r_{st}^{*,f})$ for $i = 1, ..., n$.

7. For the values of $t_i^*$, Mammen’s (1993) two-point distribution is used [18]:

$$
t_i^* = \begin{cases} 
\frac{-\sqrt{5}}{2} & \text{with probability } p = \frac{\sqrt{5}+1}{2\sqrt{5}} \\
\frac{\sqrt{5}+1}{2} & \text{with probability } (1-p)
\end{cases}
$$

(10)

3.4 SGARCH model

This model comes under the category of multivariate or multi-dimensional GARCH models. Harris, Stoj and Tucker in the year 2007 proposed a basic method of estimating parameters of the conditional covariance matrix using one-dimensional GARCH model and called it a Simplified Generalized Auto-Regressive Conditional Heteroscedasticity (SGARCH) model. The parameters of this model are estimated using univariate GARCH models. They are estimated for individual as well as sum and difference of return series. Covariance is estimated from the variance estimates of sum and difference of return series. According to Harris, Stoj and Tucker, the model for spot return based on GARCH (1, 1) model is:

$$
r_{st} = \mu + \epsilon_{st} , \epsilon_{st} = \sigma_{st} \epsilon_{st-1} \\
\sigma_{st}^2 = \sigma_0^2 + \alpha \epsilon_{st-1}^2 + \beta \sigma_{st-1}^2
$$

(11)

Where $\epsilon_{st}$ is a random number drawn from the standard normal distribution, $\mu$ is the conditional mean return, $\epsilon_{st}$ is the residual term, $a$ is the constant or the intercept term and $a>0$, $b$ is the coefficient of GARCH term and $b \geq 0$, it is the forecasted volatility from the past period, $c$ is the coefficient of ARCH term and $c \geq 0$. $\sigma_{st}^2$ is the conditional variance of $r_{st}$ and is based on the information known up to the time $t-1$. The covariance-stationary condition for GARCH (1,1) process is $b + c < 1$. $b + c$ gives the level of persistence.

Similarly, the model for future return is

$$
r_{ft} = \mu + \epsilon_{ft} , \epsilon_{ft} = \sigma_{ft} \epsilon_{ft-1} \\
\sigma_{ft}^2 = \sigma_0^2 + \alpha \epsilon_{ft-1}^2 + \beta \sigma_{ft-1}^2
$$

(12)

Using GARCH (1, 1) model $\sigma_{st}^2$ and $\sigma_{ft}^2$ can be found out. After that two series

$$
r_{st} = r_{st} + \sigma_{st} \epsilon_{st-1} \\
and
r_{ft} = r_{ft} + \sigma_{ft} \epsilon_{ft-1}
$$

are created and GARCH (1,1) is used to find the conditional variance ($\sigma_{st}^2$ and $\sigma_{ft}^2$) of these two series similar to model (11) and (12). Then the covariance between spot and future return can be calculated as

$$
\sigma_{st} = \frac{1}{4} (\sigma_{st}^2 - \sigma_{ft}^2)
$$

(13)

The minimum variance hedge ratio is given by

$$
\beta = \frac{\text{cov}(r_{st}, r_{ft})}{\text{var}(r_{ft})}
$$

4 NUMERICAL ILLUSTRATION

4.1 Data Description

The data under study is the daily closing cash and future price of CNX NIFTY50 index downloaded from nseindia.com for the period 1 Jan 2006-31 Dec 2015. Hedge ratio and hedging effectiveness are statistical techniques based on time series data, so it is necessary to consider the statistical properties of the time series under study. ADF (Augmented Dickey Fuller) test is conducted in EViews software for checking the stationarity of data (Table 1-2).

### TABLE 1

<table>
<thead>
<tr>
<th>Stationarity Test of Spot Price Series</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Hypothesis: SPOTPRICE SERIES has a unit root</td>
</tr>
<tr>
<td>Exogenous: Constant</td>
</tr>
<tr>
<td>Lag Length: 3 (Automatic - based on SIC, maxlag = 35)</td>
</tr>
<tr>
<td>t-Statistic</td>
</tr>
<tr>
<td>-----------------------------</td>
</tr>
<tr>
<td>Augmented Dickey Fuller test statistic</td>
</tr>
<tr>
<td>Test critical values: 1% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>


### TABLE 2

<table>
<thead>
<tr>
<th>Stationarity Test of Future Price Series</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Hypothesis: FUTURE PRICE SERIES has a unit root</td>
</tr>
<tr>
<td>Exogenous: Constant</td>
</tr>
<tr>
<td>Lag Length: 30 (Automatic - based on SIC, maxlag = 35)</td>
</tr>
<tr>
<td>t-Statistic</td>
</tr>
<tr>
<td>-----------------------------</td>
</tr>
<tr>
<td>Augmented Dickey Fuller test statistic</td>
</tr>
<tr>
<td>Test critical values: 1% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>


Fig. 1. Daily spot price series
Fig. 2. Daily future price series

Then the two series are made stationary by taking their log difference (Figure 3).

Fig. 3. Daily continuous nifty50 spot returns (A) and future returns (B).

ARCH-LM test in EVIEW software is performed to check the significant ARCH effects in return series (Table 3).

### TABLE 3
ARCH TEST OF NIFTY50 RETURNS

<table>
<thead>
<tr>
<th>Heteroskedasticity Test: ARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistic</td>
</tr>
<tr>
<td>Prob. F(1,116)</td>
</tr>
<tr>
<td>Obs*R-squared</td>
</tr>
<tr>
<td>Prob. Chi-Square(1)</td>
</tr>
</tbody>
</table>

Monthly average of spot and future return has been taken as hedging horizon. The descriptive statistics of the returns series is given in Table 4.

### TABLE 4
DESCRIPTIVE STATISTICS OF NIFTY50 RETURNS

<table>
<thead>
<tr>
<th>NIFTY50</th>
<th>Spot/cash returns</th>
<th>Futures returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.00834</td>
<td>0.00945</td>
</tr>
<tr>
<td>Median</td>
<td>0.01885</td>
<td>0.01866</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>0.0605</td>
<td>0.06191</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.99344</td>
<td>3.54815</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.85057</td>
<td>-0.77746</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.27033</td>
<td>-0.26776</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.18146</td>
<td>0.18809</td>
</tr>
<tr>
<td>Sum sq.dev.</td>
<td>0.43192</td>
<td>0.45221</td>
</tr>
<tr>
<td>Count</td>
<td>119</td>
<td>119</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>84.74522</td>
<td>67.27746</td>
</tr>
<tr>
<td>Probability</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

The value of skewness and kurtosis indicates fatter tails and higher peak value around the mean. This shows that the return distribution is non-normal. Jarque-Bera test statistics also reveal that the data is non-normal. Due to non-normality and heteroskedasticity in the data, SGARCH model is used. Wild bootstrap and SGARCH methodology discussed in section 3 is applied to form a series of hedge ratio and corresponding hedged portfolio. The 10th, 25th, 50th, 75th and 90th percentiles of the hedge ratio series are evaluated in case of bootstrap methods and then hedged portfolios are constructed. Parameters like mean, variance, semi-variance, hedging effectiveness, interquartile range and 95% confidence interval are evaluated for both strategies. Comparative analysis is done based on two methods under the criteria variance or volatility, semi-variance, hedge ratio and hedging effectiveness.

### 4.2 Results and Discussion

In this segment, results from the hedging strategies based on bootstrap methods and SGARCH model are presented. To reduce the risk of spot portfolio, investments of both spot and future markets are merged to form a hedged portfolio. For this daily spot and future prices of CNX NIFTY50 index from 1 Jan 2006 to 31 Dec 2015 are taken. Result of ADF unit root test (Table 1,2) indicates that the spot and future price series is non-stationary. They are made stationary by taking log difference of spot and future price. ARCH test results (Table 3) indicates that there are significant ARCH effects in the data at 5% level of significance. In this article, average spot price return is taken as the return of unhedged portfolio. Table 4 shows the descriptive statistics of the data. The negative value of skewness shows fatter tails and the value of kurtosis reveals higher peak values. JB test shows that the data is non-normal. The Pearson correlation coefficient indicates that cash and future market returns are highly correlated. Monthly average of daily data is taken as hedging horizon. The results of the proposed methodology is given in Table 5. The hedge ratio of SGARCH hedging strategy accounts for 0.978028 which is minimum in all the strategies under study. This implies that hedging with SGARCH strategy requires less future contracts to reduce the risk of spot portfolio. Also the variance and semi-variance are minimum in case of SGARCH hedging. The estimates from hedging effectiveness clearly vote for SGARCH strategy as higher hedging effectiveness, more robust will be the hedging strategy. Interquartile range (IQ) and 95% confidence interval indicate high variability in the hedged returns based on the wild bootstrap method. The results from SGARCH hedging strategy are more consistent than the bootstrap methods.
### 4.3 Comparative Analysis

On comparing SGARCH and wild bootstrap methods, hedging through SGARCH model provides more consistent results than bootstrap methods. As the main parameters of hedging are hedge ratio and hedging effectiveness, SGARCH model provides the least hedge ratio and higher hedging effectiveness. The measure of risk i.e., variance and downside risk i.e., semi-variance is also minimum in SGARCH model. On comparing the two bootstrap methods, the results from pair bootstrap are more reliable.

## 4 CONCLUSION

This research illustrates and compares hedging effectiveness using SGARCH model and wild bootstrap percentile method. In wild bootstrap method, percentiles of the optimal hedge ratio are calculated within 95% confidence interval and parameters like mean, variance, semi variance, hedge ratio, hedging effectiveness, interquartile range are calculated and compared with the same parameters calculated through SGARCH model. The percentile bootstrap method provide a range of hedging strategies and is found to be more effective than the traditional OLS method of hedging which is based on a single point estimate. The wild bootstrap method consist of two sub methods: one based on residual resampling and the other on pair resampling. In this study, daily closing spot and future price of the CNX NIFTY50 index is taken from nseindia.com for the period 1 Jan 2006 to 31 Dec 2015. On comparing the strategies, SGARCH model outperforms wild bootstrap percentile method. On comparing the residual resampling and paired resampling, paired resampling outperform residual resampling. In terms of hedge ratio and hedging effectiveness, SGARCH model performs best. The empirical results supports SGARCH models for efficient hedging. The findings of this research prove to be helpful for market players in risk management and financial decisions.

## REFERENCES


### TABLE 4

Descriptive Statistics of NIFTY50 Returns

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Variance</th>
<th>Semi variance</th>
<th>Hedge ratio</th>
<th>Hedging effectiveness in %</th>
<th>Interquartile range</th>
<th>95% range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unhedged</td>
<td>0.008338</td>
<td>0.003660</td>
<td>0.003630</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SGARCH hedge</td>
<td>0.000075</td>
<td>0.000067</td>
<td>0.000006</td>
<td>0.978028</td>
<td></td>
<td>0.062955</td>
<td>0.010865</td>
</tr>
<tr>
<td>10th percentile</td>
<td>-0.00324</td>
<td>0.00059</td>
<td>0.000584</td>
<td>1.341256</td>
<td>83.88</td>
<td>0.0281994</td>
<td>0.004761</td>
</tr>
<tr>
<td>25th percentile</td>
<td>-0.00365</td>
<td>0.0003229</td>
<td>0.0003241</td>
<td>1.893603</td>
<td>91.18</td>
<td>0.061853</td>
<td>0.007060</td>
</tr>
<tr>
<td>50th percentile</td>
<td>-0.00367</td>
<td>0.003105</td>
<td>0.013056</td>
<td>2.81481</td>
<td>91.52</td>
<td>0.120609</td>
<td>0.10007</td>
</tr>
<tr>
<td>75th percentile</td>
<td>-0.003684</td>
<td>0.0004666</td>
<td>0.029434</td>
<td>3.734759</td>
<td>87.27</td>
<td>0.179411</td>
<td>0.012268</td>
</tr>
<tr>
<td>90th percentile</td>
<td>-0.003887</td>
<td>0.0005603</td>
<td>0.042411</td>
<td>4.287106</td>
<td>84.69</td>
<td>0.214691</td>
<td>0.013442</td>
</tr>
<tr>
<td>10th percentile</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25th percentile</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>50th percentile</td>
<td>0.001164</td>
<td>0.00020</td>
<td>0.000017</td>
<td>0.980951</td>
<td>94</td>
<td>0.005706</td>
<td>0.011309</td>
</tr>
<tr>
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<td>0.001164</td>
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