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Symmetric and Asymmetric Volatility Clustering Via GARCH Family Models: An Evidence from Religion Dominant Countries

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Volatility clustering and asymmetry are considered as an essential element in time series data analysis for portfolio managers. This study is conducted to analyze the volatility clustering and asymmetry occurrence by employing different GARCH models. Data is collected from 11 Religion Dominant Countries (RDCs) based on daily stock returns from 2011 to 2017. The findings of the study show that volatility clustering increases the asymmetric comportment of daily stock market returns. We estimated the analytical competence of GARCH models and found that GJR-GARCH and EGARCH executed better results than GARCH (p, q) in RDCs stock markets. It also shows that GJR-GARCH and EGAECH explain the asymmetric behavior along with an accurate assessment of volatility clustering for the selected 11 RDCs stock markets. This study helps managers, investors, and corporations to make investment-related decisions.

Keywords: Volatility Clustering, Religion Dominant Countries, Market Returns, Asymmetric Behavior, GARCH, GJR-GARCH, EGARCH

INTRODUCTION

For the past few years, international stock index returns have effect expressively, especially in the event of high volatility (Nadal, Szklo, & Lucena, 2017). The instability of the stock index is associated with risk management, asset pricing, and fund provision. Market volatility got vital importance for the investors and fund managers (Martens & Zein, 2004), especially when it relies on its estimation as an indicator of financial market and economy vulnerability (Abbas, McMillan, & Wang 2018). Officer (1973) found that the stock market of the US in mid nineteens remains high, especially during the events of World War II and OPEC shocks of oil.

In the present context, volatility, forecasting or risk management are significant matters in the financial world (Corradi, Distaso, & Mele, 2013). Financial decision making and volatility forecasts play a crucial role in the financial market. Usually, corporate decision makers use volatility GARCH models to check risk management and derivatives pricing. Whereas, other policymakers use this to have an eye to check the monetary and fiscal policy (Lubrano, 2001). Ang & Bekaert (2006) noticed that stock market volatility changes and varies from time to time, and just because of this volatility clustering exists. Fluctuation in volatility, indicating the lower level and high level of volatility is known as volatility clustering.

Goh, Tan, Khor, and Ng, (2016) and Balcilar, Demirer, and Hammoudeh, (2014) also reported that volatility of stock market affects the investors buying and selling power as high volatility is good for the investors whereas low volatility is hated by the investors. Apart from such dynamic overreaction influence market volatility (Lai, 2012). Therefore, it becomes essential for managers to find out the effect of volatility and risk patterns for better financial planning and decision making.

Hashmi and Tay (2007) stated that investors are still unaware to know which variable resulted in stock price volatility and therefore argue that these are exogenous issues that do not reflect asset pricing. A large experimental work found for the instability of stock returns. Gallicchio et al., (2008) used monthly data comprising of almost 30 years' data of the USA stock market found that stock market volatility influences due to various factors. Many advance studies detect the conduct of stock profits, e.g. Abbas et al., (2018) found conditional volatility in G7 countries. However, for optimal investment decisions and budget forecasting more advanced and reliable measures of risk are required.

Therefore, the reliable and optimal measure of risk is of keen importance. Previously, researchers measure risk based on the unconditional standard deviation of returns (French & Roll 1986; Schwert, 1989). However, modern researchers extended the literature and emphasized on the significance of advanced GARCH family models for volatility and risk measurement (Lanne & Saikkonen, 2007; Petit, Lafuente, and Vieites 2019; Whitelaw, 1994). This study fulfills the need for optimal measures of risk to stimulate stock market volatility by using symmetric and asymmetric GARCH models and by comparing various GARCH models will contribute to the literature in this regard. It also helps the investors by allowing them to know what types of risks present in developing and emerging markets and help them to choose appropriate diversification, asset pricing, and cautious investment decisions.

It has been noticed that religion has played a prominent role in influencing financial thought of the investors (Kumar, Page, & Spalt, 2011). The Current economic theory also focused on studying the impact of religious beliefs on financial decision making. Previous studies also investigated the role of religious principles on investment decisions, portfolio construction and asset management (Dolansky, & Alon, 2008; Lu, & Chan, 2012; Nadal et al., 2017). Iannaccone (1998) explained that religion had been connected to a huge variety of communal choices. Lu and Chan (2012) believe faith clarifies the difference in creditor privileges and the implementation level. Hilary and Hui, (2009) identified the role of religious beliefs, cultural norms and social standards on stock market volatility and found a significant effect on corporate risk-taking decisions. Therefore, it becomes necessary to consider the effect of religious beliefs on volatility clustering of stock market returns.

The study is conducted to investigate the stock market volatility of Religion Dominant Countries (RDCs) through GARCH Model. The findings have a positive impact and implications in recent modern theory like decisions hedging and optimal portfolio allocations. The distinctive feature of this research is the large data set and the targeted market. This study will help us to minimize the risk, return as well as help in global diversification. This is the good or transmitting message to all investors about the instability risk measures in religion dominant countries.

Moreover, for all the policymakers, it is a great concern in developing regulation in the countries or by taking other measures to check volatility. According to the best of our knowledge, this is probably the first study to be conducted to measure the stock market volatility by targeting complete world stock markets after appending the slot of 80% population on based of dominant religion countries.

Further, this study will contribute to the emerging literature of portfolio management in the following ways: *Firstly,* the contribution in finance literature is the model through which we can measure the volatility of daily stock markets. *Secondly*, it shows that the uneven GARCH representations are improved to exemplary volatility than symmetric GARCH (1, 1) in the case of RDC stock markets. For the investment policy formulation this research provides a proposition for depositors, investors (Individual entities, monetary and financial director's corporations and companies) whereas, for the different investor they think that high volatility is a good thing to invest in a stock market whereas low volatility is hated by investors. So, this study helps individual investors as well for the other managers and stockholders.

LITERATURE REVIEW

Investors are always willing to maximize their earnings and mitigate risk distribution from abnormal events through investment in the segmented market, but for the integrated market, this would be fruitless. However, some researchers argued that in emerging (even in developed) markets, when the competition rises then the efficiency of local markets also enhances which in return reduced the cost of capital and price instability and ultimately resulted in monetary development (Chabi-Yo et al., 2018; Hashmi & Tay 2007; Patton & Sheppard 2015).

According to Petit et al., (2019), three phenomena are observed, which included volatility clustering, Leptokurtosis and leverage effect. Ang & Bekaert (2006) believes that the current incidents have an impact on the stock market returns and increases the volatility risks. In the absence of volatility clustering asset optimization is not possible. Previous studies stated that the daily stock market has more volatility clustering as compared to weekly or monthly volatility (Nadal et al., 2017).

Volatility clustering is also explained as the unpredictable behavior of financial time series data; the results show that previous day volatility has a great impact on next day volatility if the previous day has high volatility then next day volatility also increases (Chinzara, 2011). In this regard, Homoscedasticity is not an appropriate model to explain the level of volatility in the financial data because this model carries the assumptions of non-constant behavior in daily time series data. Therefore, in this situation, GARCH models are suitable to check the effect of these non-constant data (French & Roll 1986). GARCH models are suitable to check the level of volatility and risk measurement (Corradi et al., 2013).

Many researchers debated the direction of the relationship between volatility and return. Some people believe in the existence of a negative relationship due to the principle of high-risk, high return or low-risk low return, i.e., inverse relationship between volatility and return. (Do, Brooks, Treepongkaruna, & Wu, 2016; Gabrielsen, Kirchner, Liu, & Zagaglia, 2015). News symmetrically affects either positively or negatively on volatility. Volatility clustering is important in many ways like it helps in measuring asset's volatility variation, useful in financial time series, useful in measuring kurtosis risk — dynamics of asset's volatility variation (Coskun & Ertugrul, 2016).

Bouchaud, Gefen, Potters, and Wyart (2004) used a micro model to study volatility through different models. They used ARCH models to check the volatility in stock markets. Researchers found a positive effect between volatility and return. They indicated that ARCH effect exists in stock markets that were found by volatility clustering and lepto-kurtosis. Tseng and Li (2012) and Schwert, (1989) studied the financial time series to find out the influence of volatility on time with the help of ARCH models through volatility clustering and kurtosis and confirmed the direct relationship between them. They argued if volatility clustering is high in the data, then it indicates that kurtosis is also high. With the help of various asymmetry models, they compared the forecasting power of various volatility models. Their finding also indicates that an increase in the volatility also increases the kurtosis and asymmetry or risk. Their results further depict that if there exists a negative clustering impact, which is more than positive clustering, then it leads towards asymmetric distribution rather than Gaussian distribution.

The mean GARCH method is the distribution of measurement of skewness tested by Lanne and Saikkonen, (2007). Harvey and Siddique (2000) explore the volatility and skewness to check the effect of stock market volatility, Hansen and Lunde (2005) found that there is no appropriate models existed to check the effect of stock market volatility, so their study found that best model that fit to check volatility is GARCH Model. The current study tries to bridge this gap by analyzing the volatility through GARCH model by targeting global stock markets on the basis of religious dominance.

RESEARCH METHODOLOGY

The current study finds the effect of RDCs on stock market volatility through GARCH models. Data is collected from MSCI (Morgan Stanley Capital Index) from 2011-17. According to the scope of the study, only RDCs of the world are included. RDCs are for this study are those countries where a specific religion dominates (80% or above population are the believers of a specific dominant religion) (Nadal et al., 2017). Therefore, based on this rule, the sample countries were 49.

We further apply sample selection rules, *Firstly* 37 countries are not considered due to unavailability of data *Secondly,* eliminated one country from the sample whose stock market is not volatile (Confirmed from ARCH, GARCH, EGARCH, and GJRGARCH tests). Finally, end up with a total of 11 sample countries with the balance panel data from 2011 to 2017.

a. Construction of Mean Equation and application of GARCH Models:

ARCH was introduced in 1982 by Engle with a conditional variance that converted ARCH to GARCH. GARCH acted as one of the significant ways to analyze the volatility of daily stock returns of RDCs. This study applies the autoregressive method, where returns are the main function. The basic purpose of applying the integration of AR (1) term Φ1Rt- 1 is its authenticity and validity by previous researchers.

$R_t = \emptyset_0 + \sum_{i=1}^{k}\emptyset_1 R_{t-1} + \mu_t$ .... (1)

While

$\mu_t = \sum_{i=1}^{p} Pi\, \mu_{t-1} + \sum_{i=1}^{q} qi\, \mu_{t-1} + \epsilon_t$

b. Variance Equation and its construction.

To measure the stock return volatility, firstly, apply ARCH Models.

$$\sigma_t = \omega + \alpha \in_{t-1} + \beta\sigma_{t-1}$$
$$\sigma\, _t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Above equation shows that σ_t^2 is written as h_t that is the variance of residuals resulting from the above mean calculation on present-day instability of the individual stock market. Provisional alteration can be shown as follows:

$h_t = \omega + \sum_{i=1}^{q}\alpha_i \in\, _{t-i}^{2} + \sum_{j=1}^{p}\beta_i\, h_{t-j}$..... (2)

Where

$$\omega > 0, \alpha_i \geq 0\ and\ i = 12345 \ldots\ldots p$$

h_t is the current day variance from the above equation (1).

Whereas

$\in\, _{t-j}^{2}$ is the last day squared residuals from equation (2). With the help of these two findings, we further use the ARCH model to measure the effect of volatility.

c. Symmetric GARCH Model and its Restriction.

GARCH (σ_t^2) is a considered a better model to understand the large shocks and volatility clustering as compare to ARCH (Patton & Sheppard 2015). GARCH models have some major restriction as it assumes asymmetric volatility, whatever is the possibility of negative or positive shocks (Lubrano, 2001). Whereas ARCH and GARCH are the more appropriate measurement for risk than descriptive statistics in the presence of frequent fluctuations in stock returns when the symmetric distribution is extraordinary (Ang & Bekaert, 2006). On the contrary, the variance is a reliable measure for positive volatility, which is not reviled by the stockholders. The problem of instability and unequal distribution of stock returns. To avoid asymmetric instability; this study runs different models for measurement of GARCH (GJR- GARCH and EGARCH) for explaining of asymmetry:

$\sigma_t = \omega + \alpha\sigma_{t-1}|\in_t| + \beta\alpha_{t-1}$

$\sigma_t = \omega + \alpha\sigma_{t-1}|\in_t - b| + \beta\alpha_{t-1}$

$\sigma_t = \omega + \alpha\sigma_{t-1}[|\in_t| - c \in_t] + \beta\alpha_{t-1}$

$\sigma_t = \omega + \alpha\sigma_{t-1}[|\in_t - b| - c(\in_t - +\beta\ \alpha_{t-1}$

Where

$\int(\in_t) = |\in_t - b| - c(\in_t - b)$

d. EGARCH and GJR-GARCH Model and Derivations of Asymmetric.

In this study, we run different GARCH models for risk measurement along with the distress signs as per previous researchers these signs may be positive as well as negative it depends upon the GARCH effect (Chabi-Yo et al., 2018; Nelson, 1991). Below model helps to understand the skewness of shocks, either positive or negative.

$$X_t = \exp(\frac{h_t}{2})\ \varepsilon_t$$

Whereas

$$h_t^2 = \gamma_0 + \gamma_1 h_{t-1} + g\ (\epsilon_{t-1})$$

While

$$g\ (x) = \omega x + \lambda\ (\ |x| - E|x|)$$

This can be written as

$$h_t = \omega + \sum_{i=1}^{q}\alpha_i \left|\frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}}\right| + \sum_{j-1}^{p}\beta_j \log h_{t-1} + \sum_{k=1}^{r}\gamma_k \frac{\epsilon_{t-k}}{\sqrt{h_{t-k}}}$$

(3)

GJR-GARCH is the extended type of GARCH (p, q) that is used to measure additional asymmetric risks.

$$h_t = \omega + \alpha_i\epsilon_{t-i}^2 + \gamma_i\epsilon_{t-i}^2\, I_{t-i} + \beta_j\, h_{t-j}$$

After confirming the stock market volatility, in the next part, we analyze the impact of religious conviction on stock market prices.

APPLICATION OF GARCH MODELS

Before running the GARCH models, this study checks the stationarity in data through the Augmented Dickey-Fuller (ADF) unit root test.

Table 1: Unit Root Test

Countries	F-Statistic	R-squared	Prob. F	Prob.Chi-Sq
Bangladesh	94.5116	84.2915	0	0
Egypt	117.710	110.448	0	0
India	3.84083	3.83674	0.049	0.049
Indonesia	121.704	113.953	0	0
Pak	41.8917	40.9946	0	0
Romania	69.7508	67.2515	0	0
Saudia	144.979	134.435	0	0
Taiwan	89.4783	85.3313	0	0
Thailand	35.5165	34.8404	0	0
Tunisia	579.924	434.895	0	0
Turkey	22.3009	22.0470	0	0
Venezuela	0.00072	0.00072	0.9785	0.9785

Above table for Unit root test shows that data is stationarity except for Venezuela because the P value of Venezuela is 0.9785, which shows that we cannot further apply GARCH models to check the stock market volatility. This P value is greater than 5%, so we exclude this country from the sample size because we cannot further run different GARCH models as this P value is not significant.

Table 2: GARCH Model

Coeff.	Bang	Egp	Ind	Indo	Pak	Rom	Sau	Tai	Thi	Tun	Tur
Mean Eq.											
Φ0	**-0.0**	**-0.0**	**5E-0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Φ1	**-0.2**	**-0.0**	**0.0**	**0.0**	**0.1**	**0.0**	**0.1**	**0.0**	**0.0**	**0.2**	**-0.0**
Var. Eq.											
Ω	**0.0**	**9E-0**	**8E-0**	**0.0**	**0.0**	**5.3E-0**	**5.1E-0**	**1.6E-0**	**6.8E-0**	**2.7E-0**	**9.5E-0**
A	**1.7**	**2.1**	**0.0**	**0.1**	**0.1**	**0.1**	**0.1**	**0.0**	**0.1**	**0.20**	**0.08**
B	**0.3**	**0.3**	**0.9**	**0.8**	**0.7**	**0.7**	**0.7**	**0.9**	**0.89**	**0.66**	**0.86**

This study depicts the findings of GARCH (1, 1) for daily stock market data of the selected stock markets. Table 2 results are based on estimated parameters of GARCH α, and β that are statistically significant at 1% level of significance and positive for all RDCs. The daily frequency data estimated β parameter is ranging from 33% to 94% maximum in India, that is 94% and positive show high nonstop volatility. While β constraint is low in Egypt, which shows moderately low unceasing volatility. Similarly, α is also important and checked at a 1% level of significance. The values of α and β in daily data set is more than 97 % but less than 1 in each market that expresses high volatility clustering in the RDCs stock market.

Table 3: E-GARCH

Coeff.	**Bang**	**Egp**	**Ind**	**Indo**	**Pak**	**Rom**	**Sau**	**Tai**	**Thi**	**Tun**	**Tur**
Mean Equation											
Φ0	**-0.000**	**-0.00**	**3E-0**	**-0.00**	**0.00**	**0.00**	**0.00**	**-0.00**	**0.00**	**0.00**	**0.00**
Φ1	**-0.234**	**-0.00**	**0.08**	**0.03**	**0.18**	**0.10**	**0.17**	**0.04**	**0.06**	**0.24**	**-0.01**
Variance Equation											
Ω	**-1.25**	**-1.30**	**-0.22**	**-0.47**	**-1.14**	**-1.056**	**-0.79**	**-0.26**	**-0.34**	**-1.54**	**-0.54**
A	**1.10**	**1.18**	**0.07**	**0.23**	**0.24**	**0.31**	**0.24**	**0.07**	**0.16**	**0.35**	**0.13**
B	**0.43**	**0.49**	**-0.08**	**-0.08**	**-0.201**	**-0.09**	**-0.16**	**-0.109**	**-0.10**	**-0.05**	**-0.08**
Γ	**0.92**	**0.92**	**0.98**	**0.96**	**0.900**	**0.91**	**0.93**	**0.97**	**0.97**	**0.88**	**0.94**

Table 3 shows the EGARCH results of the valued constraints of day to day statistics of selected markets. Our α parameters in above-mentioned RDCs is P=1%. Empirical results of EGARCH is a measure of symmetric and asymmetric volatility that helps to check or find out the impact of volatility clustering of stock returns in the selected RDCs. The logarithm requirement makes EGARCH easy to use relative to other GARCH models. EGARCH combines the past dated (day) shockwave on the logarithm of conditional volatility which is $\alpha - \beta$ (negative shock) while for optimistic shockwave or news this is $\alpha + \beta$. Sum of α and β constraints also show that long period news has less impact on instability than a short period. This has also been expected that γ should be positive or negative shockwave that impacts more or less as to compare to positive shock on variance $(\alpha - \beta > \alpha + \beta)$ in volatility modeling. The results of day-to-day data table show $\alpha\ ,\beta\ and\ \gamma$ all are significantly important at p =1%. The table shows that bad news impact more relative to good news in all marketplaces and our $(\alpha - \beta)$ is also better than $(\alpha + \beta)$ which confirms these findings.

TABLE 4: GJR GARCH

Coeff.	**Bang**	**Egp**	**Ind**	**Indo**	**Pak**	**Rom**	**Sau**	**Tai**	**Thi**	**Tun**	**Tur**
Mean Equation											
Φ0	**-0.00**	**-0.00**	**0.00**	**-0.00**	**0.00**	**0.00**	**0.00**	**-7.7E-**	**0.00**	**4.6E-**	**0.00**
Φ1	**-0.23**	**-0.00**	**0.08**	**0.03**	**0.18**	**0.10**	**0.17**	**0.04**	**0.06**	**0.24**	**-0.01**
Variance Equation											
Ω	**0.00**	**1.9E-0**	**1E-0**	**7.1E-0**	**0.00**	**0.00**	**4.7E-0**	**1.8E-0**	**1.2E-06**	**2.6E-0**	**9.6E-0**
A	**2.88**	**3.65**	**0.00**	**0.04**	**0.01**	**0.08**	**0.01**	**-0.01**	**0.02**	**0.11**	**0.01**
B	**-2.39**	**-3.17**	**0.08**	**0.12**	**0.30**	**0.15**	**0.29**	**0.12**	**0.13**	**0.14**	**0.11**
Γ	**0.35**	**0.31**	**0.93**	**0.86**	**0.75**	**0.77**	**0.80**	**0.92**	**0.89**	**0.68**	**0.87**

The above table shows GJR-GARCH results after applying the ARCH effect, the valued constraints of day to day statistics of selected markets. Our α parameters in above-mentioned RDCs is at P=1% level of significance. The β value confirms the presence of volatility in stock returns of RDCs. Above results are very much good and encouraging the reason is that all values of these above models are significant that shows that we have applied or selected appropriate models to check the volatility of daily stock returns. Asymmetric constraint γ is significant at p = 1% in all selected marketplaces, which is predictable. These results show the impact of religious beliefs on future stock returns. These results show that stock market volatility is high in the sample countries. On the other side, we see that if there is more good news impact. It means that these values have an impact on next day volatility that is decreased but bad news impact increases in nest day volatility. This is mainly as our asymmetry GARCH the constraint γ is more than α ARCH constraints of formed residuals in day to day daily data. Above table shows that $\gamma\ parameter$ is positive and significant at p = 1%.

Discussion

This study runs the GARCH Models to check the volatility by targeting 11 RDCs around the world on the basis of daily stock market prices from 2011-2017. It investigates the stock market volatility by using an optimal measure of risk to help investors, financial institutions for better investment decisions. It uses modern GARCH models for portfolio optimization and contributes to the finance literature by emphasizing the role of volatility clustering in RDCs that helps the investors as well as to the brokers and decisions makers.

The findings of the study are discussed in the following ways: *Firstly,* we check the presence of volatility through the Unit Root Test. Secondly, the volatility of the daily stock market is measured to check the fluctuation in the stock market. *Thirdly* in this study, we have checked the presence of asymmetry in daily time series data. The researchers use the Unit Root Test to check the stationarity in the data and results depict no stationarity in the data.

We excluded one country after applying the ARCH model because P value of Venezuela is more than 5% so after the stationarity test we check GARCH (1, 1) model to check the volatility, EGARCH model, GJR-GARCH models are used to check the volatility because these are the modest way to check the volatility. Previously researchers apply the traditional measure to check the volatility which is not the good approach, so we have applied these GARCH models to check the volatility.

The results show that there is volatility in the selected markets of RDCs, so these results help the investors to take an attention when they are investing in selected stock markets. It further explains that high volatility in RDCs. EGARCH also shows high volatility effect when we applied the next model of GJR-GARCH to measure the occurrence and presence of volatility in the selected data of 11 RDCs. The findings also confirm the existence of volatility among RDCs. This study contains different GARCH models to check the volatility. Study findings show that symmetric GARCH is not better, whereas our results in GARCH, EGARCH, and GJR-GARCH shows better than the symmetric GARCH.

This study provides new dimensions to the scholars as well as to the financial and portfolio managers. *Firstly,* it contributes to the finance literature of RDCs by giving lookups and models to check the volatility clustering and asymmetry. *Secondly,* it recommends that the asymmetric GARCH directions and models are better to check the volatility clustering and asymmetry rather than symmetric GARCH (1, 1) in case of RDCs. *Thirdly,* With the help of this study, investors, individuals, portfolio manager, stockholders, and other corporations and make of formulating the reporting mechanism or techniques.

Conclusion and Future Directions

This study is conducted to check symmetric and asymmetric behavior of volatility clustering in RDCs on the basis of daily stock returns from 2011 to 2017. Findings of the study show that the asymmetric GARCH shows better results than simple GARCH models. For daily time series, it explains the asymmetric volatility model as the best-suited model for asymmetric volatility. The study can act as the first step to observe the volatility behavior of the RDC's.

This study contains some limitations that are important to address in order to extend the scope of the study: *Firstly,* it uses the dataset of daily prices from 2011 to 2017. Future researchers can use extended financial data and include new models to measures the volatility clustering in the diversified stock markets. *Secondly,* it focuses on the RDCs only and uses a simple criterion to select the RDCs. There is a need to redefine and develop a selection criterion for RDCs. So future researcher can work in this area. *Thirdly,* a comparative study can be conducted to check the impact of RDC and Non-Religion Dominant countries. *Lastly,* there is the possibility of another extension to check the effect of risk or volatility through News Impact Curves. This area can be explored in future that enhances the scope of the study.

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