ACTA UNIVERSITATIS AGRICULTURAE ET SILVICULTURAE MENDELIANAE BRUNENSIS

Volume 62 143 Number 6, 2014

http://dx.doi.org/10.11118/actaun201462061373

IMPACT OF TRADING VOLUME ON PREDICTION OF STOCK MARKET DEVELOPMENT

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Abstract

PLACHÝ RUDOLF. 2014. Impact of Trading Volume on Prediction of Stock Market Development. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis,* 62(6): 1373–1380.

The paper focuses on the influence of trading volume on quality of prediction of stock market development. The main objective of this article is to assess the influence of stock trading volume level on quality of prediction with use of technical analysis. The research was applied on stocks included in the S & P 500 index. Based on average daily trading volume, three aggregate indexes were constructed.

The dynamics of index return volatility was modeled by GARCH-class models. GARCH(1,1), GJR and EGARCH models were estimated for each time series. The in-sample evidence indicated that the return volatility of the indexes can be characterized by significant persistence and asymmetric effects. The best estimate of each model was produced for the index of stocks with the highest average trading volume.

However the result could differ based on the observed period, the volatility structure of the examined data supports the idea that influential investors respond to various shocks in the market primarily by closing or opening their largest position.

The importance of the level of trading volume for the prediction of financial time series development was shown in the paper. This finding could help generate such volatility structure of time series which would allow to explain development of the time series by various models with better results.

Keywords: Stock market, trading volume, prediction, volatility, GARCH

INTRODUCTION

It is possible to track trading volume over time for every traded stock. One could suppose that stocks with higher volume are more observed up by analysts than those less traded. This could cause more accurate reflection of affecting variables in time series development.

The main objective of this article is to assess the influence of stock trading volume level on quality of prediction with use of technical analysis.

Trading volume is a very important and followed indicator. This demonstrates great attention that authors pay to related topics.

The main stream focuses on the direct relationship between trading volume and stock return (Chan, 2012). The importance of trading volume on stock market has already been known for a long time. Karpoff (1987) states that the relationship between trading volume and stock return carries information applicable for selection of appropriate theoretical model. Campbell *et al.* (1993) showed that the mentioned relationship helps with the issue of identification when testing various models. On the other hand some studies did not verify any positive relationship between trading volume and stock price (Karpoff, 1987).

Wang and Huang (2012) also dealt with a similar topic. They examined the relationship between trading volume and volatility of the Chinese stock index Hu-Shen 300 with an approach of volatility decomposition in their study. A positive correlation between trading volume and the continuous component was found. On the other hand a significant negative relationship between trading volume and the jump component was found. The authors explained this phenomenon by presence of public information in the jump component on the one hand and by presence of private information in the continuous component on the other. Kuo *et al.* (2011) and Dan *et al.* (2011) dealt with a similar topic.

Despite a large number of studied papers, one that would avoid variability of trading volume is missing. This study on the contrary deals with average level of trading volume from the long run perspective. This approach is supposed to suit better the discussed issue.

DATA AND METHODS

The research was applied on stocks included in the well-known stock index S & P 500. This option ensured an extensive and reliable data set. Time series of daily prices and traded volumes were used. Several factors were considered for selection of appropriate period for the time series.

From a statistical point of view the longer the series, the better the estimation. On the other hand, the length of the time series had to be limited as the data set contained a great number of series of daily values.

Furthermore a graphical analysis of the S & P 500 index was conducted since elimination of the greatest macroeconomic shocks was required. The index rebounded in March 2009 (the red circle in Fig. 1) after the financial crisis of 2007–2008. Thenceforward there is a long growing trend up to the last observed day.

The graphical analysis highlights a disputable situation after the summer of 2011 (orange circle in Fig. 1). The sharp drop in stock prices was due to the spreading European sovereign debt crisis (Bremer, 2011) and concerns over the slow economic growth in the United States while its credit rating was downgraded by Standard & Poor's (Puzzanghera, 2011). Increased volatility of the stock market index continued for the rest of the year.

As a compromise, given the above limitations, the period from January 2011 to June 2013 was selected. Although volatility increased in 2011, the series was not shortened as a longer period was required for a more accurate identification of models.

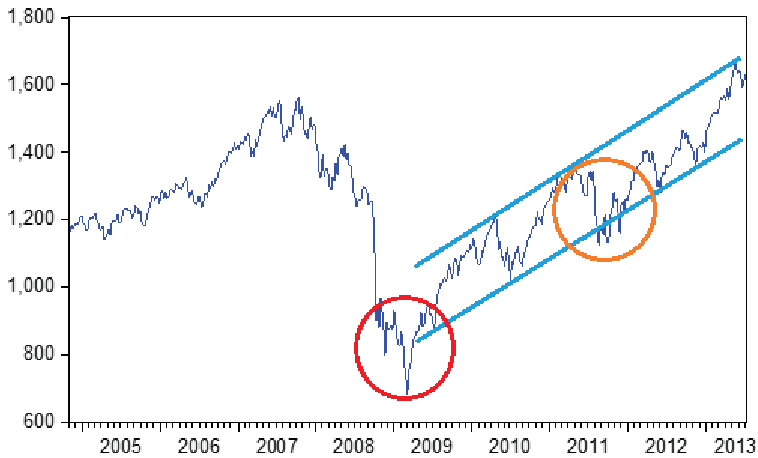
Due to the continuous adjustment of the stock index it was not possible to obtain time series of 500 stocks for the selected period. Therefore the data set was reduced to 475 time series.

In the first instance the time series of the stock prices was converted to basic indexes (Hindls *et al.*, 2007) with the basis in t0. This step enabled a convenient interpretation as well as effortless comparability of individual series developments. For each stock an average daily volume was calculated for the whole period. In the next stage all the stocks were put in the order from the largest average volume to the lowest average volume.

In the next step, three groups of companies were constructed on the basis of trading volume. Various sizes of the groups were considered. The final size was a compromise between quantity of units in each group and sufficient difference in average trade volume between the individual groups. The first group contains 51 companies with the highest trading volume, the second one consists of 51 companies from the middle of the volume rank list and the third comprises 51 companies with the lowest trade volumes from the S & P 500 index.

Furthermore an aggregate index (Hindls *et al.*, 2007) was formed for each group. Fig. 2 highlights the development of the aggregated indexes. On average, stocks in the first group (high51) climbed 36%, stocks in the second group (mid51) gained 44% while the third group (low51) grew by 24% during the observed period.

Although the differences in the average growth between the individual groups seam considerable at the first sight, disparity of averages was tested. Normality of the data was tested first. Null hypothesis of a normal distribution was rejected by both the Kolmogorov-Smirnov (p-value = 0.000) and Shapiro-Wilk (p-value = 0.000) tests.



1: *Long-term development of S & P 500 stock index*
Source: Bloomberg, EViews, own processing

2: *Development of aggregated indexes*
Source: Bloomberg, EViews, own processing

Since the null hypothesis of a normal distribution of the data was rejected, a nonparametric test had to be used for testing of disparity of the averages. The nonparametric Kruskal-Wallis test (Hendl, 2009) did not establish disparity of average growth between the groups (p-value = 0.317). Presence of influence of the trading volume level of the stocks on their growth was not proved.

Univariate GARCH-class Models

A seminal work of Engle (1982) provided the basis for the family of Autoregressive Conditional Heteroskedasticity (ARCH) models. This group of models is probably still today an unsurpassed tool for volatility modeling. Bollerslev (1986) eliminated some deficiencies of the original ARCH model by his popular GARCH (generalized ARCH) model.

Cipra (2008) describes the standard GARCH(1,1) model as follows:

$$y_t = \mu_t + e_t,\ e_t = \sigma_t \varepsilon_t,\ \sigma_t^2 =$$

$$= \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2 (\alpha_0 > 0,\ \alpha_1,\ \beta_1 \geq 0,\ \alpha_1 + \beta_1 < 1), \qquad (1)$$

where
μ_t.... denotes the conditional mean and
σ_t^2... is the conditional variance.

Glosten *et al.* (1993) proposed the GJR model to cope with effects of asymmetry. The most used form of the GJR GARCH model is:

$$y_t = \mu_t + e_t,\ e_t = \sigma_t \varepsilon_t,\ \sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 e_{t-1}^2 I_{t-1}^-,\ I_t^- =$$

$$= \begin{cases} 1 & \text{if } e_t < 0, \\ 0 & \text{otherwise.} \end{cases} \qquad (2)$$

Another approach to asymmetry was shown by Nelson (1991). His exponential GARCH model after some simplification has the form:

$$y_t = \mu_t + e_t,\ e_t = \sigma_t \varepsilon_t,$$

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 \left| \frac{e_{t-1}}{\sigma_{t-1}} \right| + \beta_1 \ln \sigma_{t-1}^2 + \gamma_1 \frac{e_{t-1}}{\sigma_{t-1}}. \qquad (3)$$

GARCH(1,1) is one of the most used models of financial time series because it is capable to handle very general volatility structure using only three parameters (Cipra, 2008).

Next procedures were conducted to construct models with the best possible prediction ability for each aggregated index. As a benchmark an aggregated index of all 475 stocks was analyzed first.

Descriptive Statistics

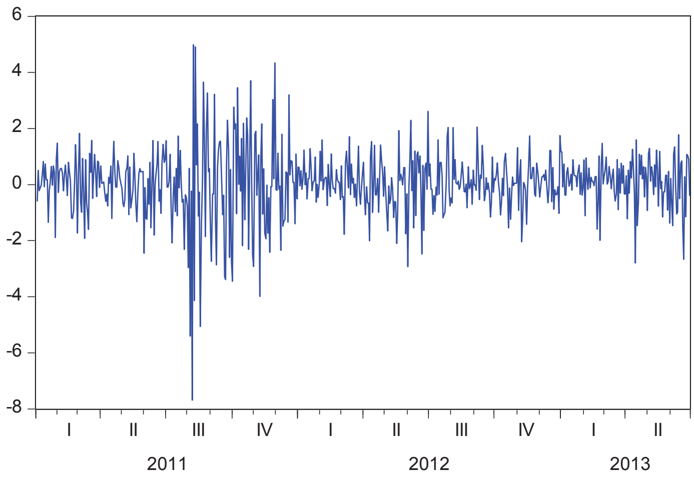
The time series of the aggregated index of all 475 stocks (all475) shown in Fig. 3 was modified to stationary Log returns (Fig. 4).

The stationarity of the returns was checked by an Augmented Dickey and Fuller unit root test. The optimal lag length of the ADF test was chosen based on Schwarz information criterion (SIC).

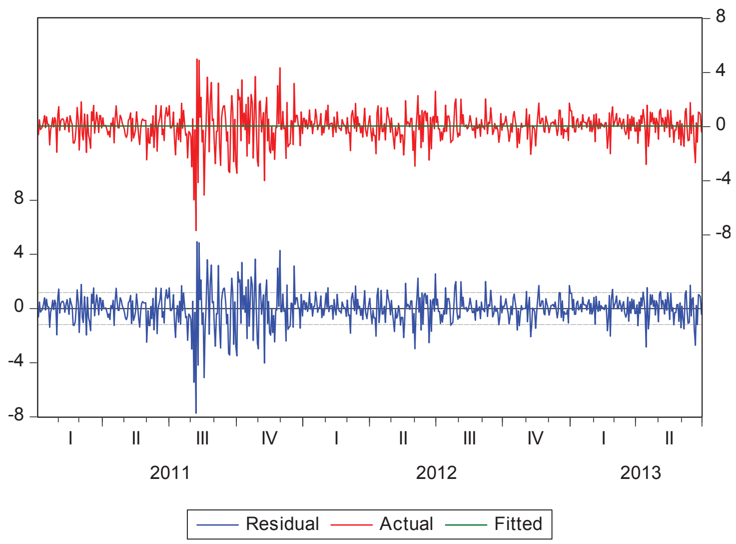
Fig. 5 shows residuals calculated as the deviation of the log returns from the mean of the series.

The Jarque and Bera statistic suggested rejection of the null hypothesis of a normal distribution of residuals at the 1% significance level. Tab. I shows that the series has a sharp and negatively skewed distribution. The null hypothesis of autocorrelation in the Breusch and Godfrey Serial Correlation LM Test was not rejected. Presence of autocorrelation was confirmed also by Ljung and Box Q statistics with the exception of the first lag. In the next step the ARCH LM test was conducted. Since ARCH was

3: *Aggregated index of all 475 stocks*
Source: Bloomberg, EViews, own processing



4: *Log returns of aggregated index of all 475 stocks*
Source: Bloomberg, EViews, own processing



5: *Residuals of the log returns time series*
Source: Bloomberg, EViews, own processing

found in the investigated data, this justifies the use of GARCH models.

The same procedure as for the variable all475 was applied on the other constructed indexes (high51, mid51 and low51). The descriptive statistics and results of the conducted tests are summarized in Tab. I. The results for all the variables are very similar.

RESULTS AND DISCUSSION

From the family of Autoregressive Conditional Heteroskedasticity (ARCH) models (Bollerslev, 1986 and Engle, 1982) three different discussed models were selected for the purpose of capturing the dynamics of volatility.

Tab. II shows the in-sample estimates for GARCH(1,1) model. High values of the estimated coefficients indicate high degrees of volatility persistence. These coefficients are all significant at the 1% significance level.

Tab. III presents the results for the GJR model and Tab. IV shows the results for the EGARCH model. For both models the asymmetric coefficients are all significant at the 1% significance level.

These results indicate existence of long-memory in the return volatility of the indexes. The numbers in parentheses are the t-statistics of the estimated coefficients.

The results of the diagnostic tests are shown in the lower part of the tables. The P-values of the statistics are reported in square brackets. Q(10) and Q(20) are the (Ljung and Box, 1978) Q statistics of order 10 and 20 respectively for the squared standardized residuals. For the series high51, mid51 and low51, Ljung and Box's Q statistics

I: *Descriptive statistics and tests*

variable	all475	high51	mid51	low51
ADF(original)	−0.760358	−0.422664	−0.915232	−0.808691
ADF(return)	−16.24726 ***	−16.37395 ***	−16.15876 ***	−16.05594 ***
mean	0.042617	0.047609	0.056467	0.033476
t-statistic	0.921379	1.130633	1.243562	0.702654
skewness	−0.618809	−0.550628	−0.552168	−0.609200
kurtosis	8.330827	7.570283	8.508805	7.964273
Jarque-Bera	809.882 ***	597.6276 ***	853.6104 ***	706.5583 ***
Breusch-Godfrey	2.187612	3.047703	1.693607	2.593459
ARCH LM test	42.23387 ***	54.49980 ***	42.62828 ***	45.25625 ***

* Denotes rejection of the null hypothesis at 10% significance level.
** Denotes rejection of the null hypothesis at 5% significance level.
*** Denotes rejection of the null hypothesis at 1% significance level.
Source: Bloomberg, EViews, own processing

II: *Estimation results of GARCH(1,1) model*

	all475	high51	mid51	low51
μ	0.070897**	0.074953**	0.089748***	0.062511*
	(2.050248)	(2.311866)	(2.650349)	(1.804224)
α_0	0.040417***	0.038697***	0.030824***	0.040256***
	(3.098134)	(3.040265)	(2.711160)	(3.028732)
α_1	0.121763***	0.113578***	0.120376***	0.123617***
	(5.861958)	(5.471435)	(6.091702)	(5.895258)
β_1	0.846299***	0.849324***	0.857747***	0.846184***
	(29.43867)	(28.38467)	(33.39167)	(30.26231)
Log(L)	-911.5064	-865.6780	-907.2702	-926.4050
AIC	2.821283	2.680055	2.808229	2.867196
BIC	2.848867	2.707639	2.835812	2.894779
Q(10)	24.529	11.231	8.4885	11.933
	[0.006]	[0.340]	[0.581]	[0.290]
Q(20)	29.055	15.097	13.296	17.946
	[0.087]	[0.771]	[0.864]	[0.591]
ARCH(10)	2.393951	2.594585	2.028940	1.965248
	[0.0086]	[0.0043]	[0.0284]	[0.0346]
ARCH(20)	1.479865	1.558572	1.317845	1.242324
	[0.0816]	[0.0573]	[0.1599]	[0.2127]
* Denotes rejection of the null hypothesis at 10% significance level.				
** Denotes rejection of the null hypothesis at 5% significance level.				
*** Denotes rejection of the null hypothesis at 1% significance level.				

Source: Bloomberg, EViews, own processing

III: *Estimation results of GJR model*

	all475	high51	mid51	low51
μ	-0.009750	0.042106	0.036356	-0.021678
	(-0.329594)	(1.417549)	(1.028179)	(-0.810476)
α_0	0.025001***	0.029338***	0.031040***	0.020462***
	(7.481759)	(6.843264)	(4.438563)	(7.227275)
α_1	-0.084204***	-0.081984***	-0.051237**	-0.091742***
	(-10.39647)	(-7.618467)	(-2.478725)	(-8.868899)
β_1	0.965560***	0.935425***	0.922928***	0.986461***
	(94.33054)	(74.39933)	(38.90089)	(101.8255)
γ_1	0.190241***	0.222453***	0.193796***	0.175142***
	(10.91542)	(8.534423)	(7.352967)	(11.21277)
Log(L)	-885.9507	-838.2380	-891.0990	-898.3067
AIC	2.745611	2.598576	2.761476	2.783688
BIC	2.780090	2.633056	2.795956	2.818167
Q(10)	7.9834	9.0164	8.5198	10.259
	[0.630]	[0.531]	[0.578]	[0.418]
Q(20)	13.174	12.668	13.091	15.337
	[0.870]	[0.891]	[0.873]	[0.757]
ARCH(10)	2.209042	1.551595	1.534680	1.860791
	[0.0159]	[0.1173]	[0.1229]	[0.0478]
ARCH(20)	1.589825	1.266573	1.079043	1.530128
	[0.0495]	[0.1945]	[0.3672]	[0.0652]
* Denotes rejection of the null hypothesis at 10% significance level.				
** Denotes rejection of the null hypothesis at 5% significance level.				
*** Denotes rejection of the null hypothesis at 1% significance level.				

Source: Bloomberg, EViews, own processing

IV: *Estimation results of EGARCH model*

	all475	high51	mid51	low51
μ	0.021787	0.023073	0.037055	0.015494
	(0.622176)	(0.753120)	(1.056870)	(0.432682)
α_0	-0.083719***	-0.086775***	-0.103278***	-0.082374***
	(-3.268576)	(-3.432350)	(-3.678984)	(-3.292036)
α_1	0.110043***	0.109187***	0.136214***	0.109041***
	(3.622944)	(3.643719)	(3.989445)	(3.655522)
β_1	0.965623***	0.957748***	0.964807***	0.969591***
	(141.4087)	(127.7045)	(112.8960)	(157.9727)
γ_1	-0.179262***	-0.189444***	-0.150699***	-0.164939***
	(-7.646491)	(-7.888340)	(-7.645125)	(-7.226013)
Log(L)	-895.0857	-847.6432	-896.1381	-912.6963
AIC	2.773762	2.627560	2.777005	2.828032
BIC	2.808241	2.662039	2.811484	2.862511
Q(10)	9.7472	9.2404	7.6285	10.661
	[0.463]	[0.509]	[0.665]	[0.385]
Q(20)	15.918	13.846	12.472	17.030
	[0.722]	[0.838]	[0.899]	[0.651]
ARCH(10)	1.242025	1.249425	1.460736	0.886406
	[0.2606]	[0.2561]	[0.1501]	[0.5456]
ARCH(20)	0.919135	1.066456	1.088002	0.770652
	[0.5626]	[0.3813]	[0.3573]	[0.7504]
* Denotes rejection of the null hypothesis at 10% significance level.				
** Denotes rejection of the null hypothesis at 5% significance level.				
*** Denotes rejection of the null hypothesis at 1% significance level.				

Source: Bloomberg, EViews, own processing

cannot reject the null hypothesis of no serial correlations at the 10% confidence level for all models. For the all475 series there is an exception in the GARCH(1,1) model where the null hypothesis is rejected even at the 1% confidence level for the Q statistics of order 10.

ARCH(10) and ARCH(20) are the 'non-heteroskedasticity' statistics (Engle, 1982) of order 10 and 20, respectively. The F-statistics and the related p-values show how well each model captures ARCH effects in returns of each time series. Arguably the best results of all the models are provided by EGARCH.

Log(L) is the logarithm maximum likelihood function value. The values of Log(L) are very close to each other across different models but across different time series they have relatively large differentials. A similar conclusion was drawn by Wang and Wu (2012) who examined returns in energy markets.

AIC is Akaike information criterion, while BIC is Bayes information criterion which are used as objective criteria and procedures for model selection (Cipra, 2008). In general, according to the information criteria the best results were achieved by the GJR model in all the time series. But the most important result for this investigation is that the lowest values of criteria were achieved for high51 series by each of the three models.

A certain level of trading volume is a generally recognized factor for forming investment strategy. Rejnuš (2010) states that the level of liquidity together with the rate of profit and risk influence demand for investment instruments. Volume is used also for price movement confirmation in technical analysis. Volume confirms power of the prevalent side of market and helps to distinguish different phases of market (accumulation, uptrend, distribution and downtrend) (Turek, 2008).

The results of this paper show that not only the level required to execute a trade can be useful for the investor. The higher the trading volume the better the possibility to predict the development of an investment instrument.

CONCLUSION

The results obtained in this paper are not in conflict with the initial assumption. The importance of the level of trading volume for the prediction of financial time series development was demonstrated.

As objective criteria for selection of a model with best attributes (i.e. particularly a low number of variables and a low value of residual component variance estimate), Akaike information criterion and Bayes information criterion were used. According to the information criteria the best results were achieved by the GJR model in all the time series. But the most important result is that the lowest values of criteria were achieved for high51 series by each of the three models.

The volatility structure of the examined data supports the idea that influential investors respond to various shocks in the market primarily by closing or opening their largest position. This finding could help analysts create such volatility structure of time series which would allow them to explain its development by various models with better results.

In light of the achieved results, market participants who use technical analysis should attain the best results of their analysis with application to the most traded stocks. The time series of the price development of these stocks should reflect new information fastest and most accurately.

In the course of time the process of globalization links financial markets all around the world. The financial time series development depends on an enormous number of independent variables. Some of them are evident but others are unidentifiable. One the one hand, market participants are forced to follow a great number of news but on the other, they are forced to seek the best possibilities of utilizing technical analyses.

A verification of the results and conclusions by application of the used procedure to other time intervals or on other stock indexes would contribute to the examined issue.

SUMMARY

This article focuses on the influence of trading volume on the quality of prediction of stock market development. Most authors examine a dynamic relationship where a time series representing the development of the stock market is the dependent variable and a time series of trading volume is an independent variable entering various models (Chan, 2012; Wang and Huang, 2012; etc.). Compared with this approach, this paper examined if a higher level of trading volume can ensure better results for constructing univariate models.

The research in this paper was applied on the stocks included in the S & P 500 index. From a statistical point of view the longer the series, the better the estimation. On the other hand, the length of the time series had to be limited as the data set contained a great number of series of daily values. As a compromise, given the above limitations, the period from January 2011 to June 2013 was selected.

Based on a calculation of average trading volume, three groups of stocks were formed and for each group an aggregate index was constructed. The graphical analyses showed that the stocks with the middle-high trading volume gained 44% on average in the observed period while stocks with the highest volume rose by 36% and those with the lowest volume strengthened only by 24%. However, the Kruskal-Wallis test did not prove presence of influence of the trading volume level of the stocks on their growth.

In the next part, The dynamics of index return volatility was modeled by univariate GARCH-class models. GARCH(1,1), GJR and EGARCH models were estimated for each time series. The in-sample evidence indicated that the return volatility of the indexes can be characterized by significant persistence and asymmetric effects. In general, according to the information criteria the best results were achieved by the GJR model in all the time series.

Finally, the results of the diagnostic tests on residuals showed that the best estimate of each model was made for the index of stocks with the highest average trading volume.

The results obtained in this paper are not in conflict with the initial assumption. The importance of the level of trading volume for the prediction of financial time series development was shown.

Acknowledgement

The findings presented in this paper resulted from grant number 20131046 "Vliv objemu obchodů na kvalitu predikce vývoje akciového trhu" (Impact of Trading Volume on Prediction Quality of Stock Market Development) of Internal Grant Agency (IGA) of the Faculty of Economics and Management, Czech University of Life Sciences in Prague.

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