OPTIMISATION OF TRADING STRATEGY IN FUTURES MARKET USING NONLINEAR VOLATILITY MODELS

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Abstract

Backtesting and optimisation of trading strategies has been widely discussed topic in practically oriented econometric analysis for many years. In this paper, we focus on application of forecasting univariate volatility models when optimizing trading strategy in futures market. This paper is focused on backtesting and optimisation of trading strategy in futures market that are based on volatility estimation using nonlinear conditional volatility models. In fact, one of the most challenging practical problems of recent years was to understand and model a behavior of volatility of financial markets. In order to illustrate an application of this approach, we consider daily returns of American e-mini market future index in the period from September 2013 to December 2014. Backtesting of trading strategy was provided by management of normalized risk and amount of contracts per trade assuming unvarying other parameters of trading strategy. When optimizing initial trading strategy using conditional volatility models a profitability has increased significantly while maintaining reasonable values of other characteristics compared to its initial values.

Key words: backtesting, futures, nonlinear conditional volatility, optimisation, risk

JEL Code: C53, C87, G13

Introduction

Information about financial markets is usually presented in the form of financial time series. Analysis of financial time series is considered a relatively new discipline. The process of globalization of financial markets has resulted in more efficient and faster movement of capital. Nowadays, it is possible to carry out transactions almost instantaneously using extensive and sophisticated information systems. It results in a sharp rise of transactions on financial markets. Therefore, investors in financial markets are increasingly focused on modeling and forecasting of future development of financial time series. The pressure on development of new methods and models that are capable to predict future development of financial data has been logically increasing.

Financial markets can be characterized by relatively high volatility in last twenty years. These fluctuations brought a greater risk for traders in financial markets who wanted to insure against increased risk. This fact led to the emergence of new financial instruments – financial derivatives. Financial derivatives are products of financial markets whose values are derived from underlying assets. Financial derivatives markets arose primarily to reduce or eliminate risk on financial markets (Jílek, 2010). Speculative trading, whose aim is to get a speculative profit, came to the fore in connection with the process of globalization of financial markets and development of information technologies (Habudová, 2015). Following the introduction of currency futures there were also derived stock index futures, interest rate futures, and a few years later also swaps (Chance, 1998).

Financial derivatives become a common tool for hedging and speculations as well. The correct prediction of the future development of asset prices brings usually higher profits. That is why; investors are usually motivated to improve continuously methods to estimate accurate future values of assets. Nevertheless, there exists a risk that a prediction will not be correct due to instability of financial markets, fluctuations in asset prices, exchange rate changes, etc. This risk can be expressed in the form of volatility. Thus, lower volatility means lower risk on market. However, low value of volatility usually corresponds to lower yield. Volatility is therefore a very important element which may significantly affect investors' decision making. Nevertheless, estimation a value of real volatility, its modelling and forecasting can be very challenging for investors.

Backtesting and optimisation of trading strategies was investigated in numerous papers, studies and research reports over last decades. Authors applied differenet approaches, methods and software when testing and optimising trading strategies not only in futures market. Gencay (1998) evaluated the predictive performance by the market timing tests of Henriksson-Merton and Pesaran-Timmermann to measure whether forecasts have economic value in practice or not. Tian et al. (2012) applied a trading strategy based on the combination of ACD rules and pivot points system into Chinese market. They suggested an improvement of this widely used strategy providing the calculating and optimizing methods in detail to verify its efficiency using data from Chinese futures market. Harvey and Liu (2015) adjusted standard evaluation methods for multiple tests. Sharpe ratios and other statistics were overstated in this paper. Their methods are simple to implement and allow for the real-time evaluation of candidate trading strategies. However, it is impossible to find a sophisticated study or paper that utilized volatility models when optimising trading strategy in futures market. This approach seems to be a novelty.

That is why, the aim of this paper is backtesting of trading strategy in futures market and its optimisation using nonlinear conditional volatility models. Optimization of strategy will be provided using management of normalized risk and amount of contracts per trade assuming unvarying other parameters of this strategy. For the purposes of this paper there will be used daily returns of American e-mini market index in the period from September 2013 to December 2014.

1 Volatility Models

This chapter describes selected model that will be applied to model and predict a volatility. There exist several approaches how to estimate and forecast volatility of financial time series. For the purpose of this contribution there will be utilized conditional volatility model. In classical financial literature, conditional volatility models belong to one of the most frequently used approach to model a dispersion of data from financial markets. The original autoregressive conditional heteroskedasticity model (ARCH) was defined by Engle (1982). ARCH model was later extended and modified by Bollerslev (1986) and other authors as well.

One of the main limitations of linear ARCH model is the fact that this model doesn´t take into account asymmetric impact of positive and negative news on volatility. It is due to the fact that the conditional variance in ARCH model is a function of the squares of the residuals. Therefore, linear models don´t reflect their signs. That is why, it is necessary to enter into the field of nonlinear models for the purposes of our analysis. Asymmetric models of conditional variance can capture the different effects of positive and negative shocks to volatility. In other words, to model this phenomenon we have to apply for some nonlinear model which allows us to analyse an impact of asymmetric shocks on volatility (Seďa, 2011).

Nelson (1991) defined conditional volatility model named Exponential GARCH that allows for asymmetric effects. This model may solve one of shortcomings of symmetric conditional volatility models. While symmetric GARCH model imposes the nonnegative constraints on the parameters of this model, Exponential GARCH (EGARCH) models the logarithm of the conditional variance. Conditional variance in EGARCH(p,q) model can be written as follows:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right), \tag{1}$$

where ω is a constant term. Other parameters can be explained as follows: for instance σ_{t-1}^2 represents last period's forecast variance and ε_{t-1} denotes news about volatility from the previous period that is measured as the lag of the squared residual. It should be noted that the left-hand side is the logarithm of the conditional variance. The leverage effect is naturally exponential. It implies that forecast of the conditional variance is guaranteed to be nonnegative. The presence or absence of leverage effects can be verified by the hypothesis that $\gamma_k < 0.$ It was empirically observed that bad news can have a larger impact on volatility (Seďa, 2011), so that the value of γ_k would be expected to be negative. To sum up, the EGARCH model basically models the log of the variance as a function of the lagged absolute errors from the regression model and the lagged logarithms of the variance.

2 Data Sample

In this chapter, the data file that will be utilised in the empirical part of this paper will be described. Stock indexes of futures markets and especially e-mini markets of these derivatives belong to the most liquid financial markets. E-mini markets are contracts on stock indexes, which usually contain smaller amounts of financial instruments. These financial instruments reduce not only risk for investors but also trading and transaction costs. Important is also the fact that it is possible to deal with significantly less capital on e-mini markets comparing to standard stock markets.

When choosing a market in which we are planning to trade, one of the basic selection criteria is market volatility. Other important criteria may include market liquidity and margin requirements. The value of margin usually depends on the type of market instrument traded. Before opening a position in this market, it is necessary to embed an initial margin. This is a refundable deposit which allows you to control future contracts. The value of the initial margin is usually set at 5-10% of the contract value. This value is usually determined by stock exchange. There is further specified maintenance margin for each contract that is the minimum available balance on the merchant account (Habudová, 2015).

The initial amount of capital for opening an account usually ranges from 5 000 USD and 10 000 USD. A fee for trading command varies from 5 USD to 10 USD. For the purpose of this paper, it was chosen e-mini market labelled by symbol YM which is derived from Dow Jones Industrial Average (DJIA) index. This asset is traded on the Chicago Board of Trade (CBOT). Basic testing period is more than one-year long. It starts on the 25th of September 2013 and ends on the 12th of December 2014. This testing period includes in total 309 trading days. Analysed time series is adjusted to exclude weekends and holidays. Table 1 summarizes basic characteristics of analysed trading strategy, including the value of initial account, margin, broker fee for trading command, values of profit target and stop loss.

Tab. 1: Basic characteristics of trading strategy

Time Series	YM
Testing Period	25. 9. 2013 - 12. 10. 2014
Number of Trading Days	309
Initial Account	10 000 USD
Initial Margin	500 USD
Broker Fee	10 USD
Profit Target	80 tick = 400 USD
Stop Loss	50 tick = 250 USD
Entry	Pattern, momentum
Exit 1	Profit target
Exit 2	Stop loss

Source: Habudová (2015), modified by author

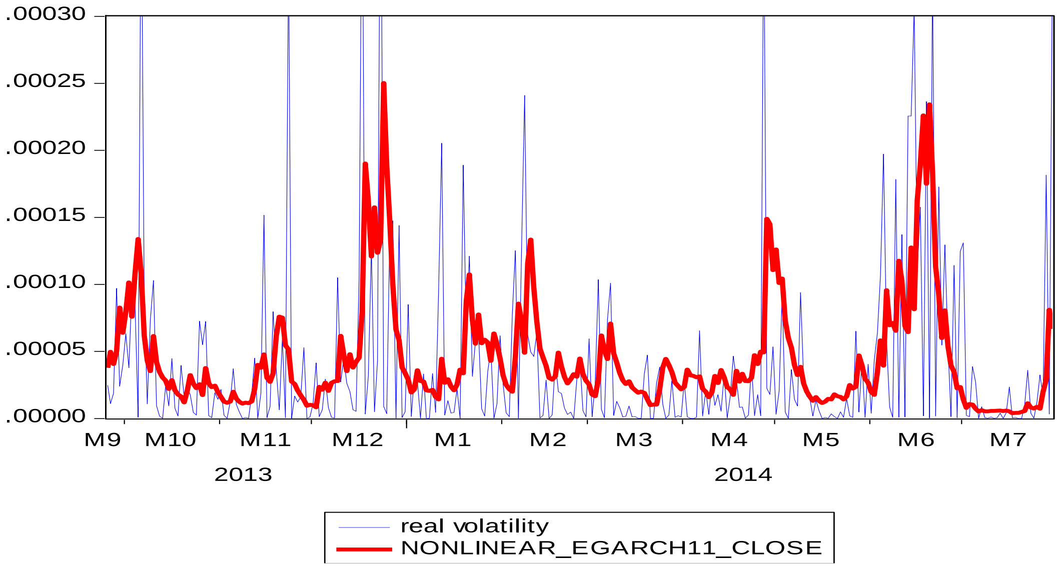
Defined parameters of trading strategy will be applied on YM time series in Chapter 4. Demo version of specialised software *NinjaTrader7*, which is a useful tool for further analysis and optimization of trading strategy, will be applied for the purpose of this paper. Moreover, it is possible to record all information relating to trades completed with a help of *PSTradebook*. In particular, one can observe a number of the transaction, date and exact time of entry or exit into/from position, tick volume, indicator MAE (Maximum Adverse Excursion), MFA (Maximum Favourable Excursion), value of earned profit in USD, account status, risking amount in % and so on.

3 Estimation of Volatility

In this chapter, there will be estimated best nonlinear conditional model which was defined in Chapter 1. In addition to this, estimated results will be graphically presented and compared with real or actual values of volatility that are approximated by squared returns. Backtesting of trading strategy was conducted before its optimization and subsequently after optimization as well. Optimisation of trading strategy in Chapter 5 was therefore carried out on the basis of estimation of best nonlinear conditional volatility model.

Estimation of best nonlinear conditional volatility model was realized on time series of historical daily closing prices of YM assets in the period from September 2013 to December 2014. Volatility was estimated with a help of Eviews software. When estimating volatility of future market, the next step is to provide analysis of residual term. That is why, Jarque-Bera test of normality, Ljung-Box test of autocorrelation and Engle´s test of heteroskedasticity were carried out for standardised residuals. Performed diagnostic tests of residual term as estimated by EGARCH(1,1) model have not identified a presence of autocorrelation or heteroskedasticity in residual term. Moreover, the null hypothesis of normality cannot be rejected on the basis of Jarque-Bera test of normality. Figure 1 shows volatility as estimated by EGARCH(1,1) model that is in a graphical way.

Fig. 1: Comparison of volatility estimated by EGARCH(1,1) model and real volatility



Source: Habudová (2015), modified by author

Bold line in Figure 1 shows the development of conditional volatility as modelled by nonlinear EGARCH(1,1) model while thin line represents real volatility approximated by squared returns. It is clear that estimated nonlinear conditional volatility model relatively plausibly fits the development of real volatility. It can be concluded that estimated EGARCH(1,1) model is suitable for application on real data when testing and optimizing trading strategy of YM future.

4 Backtesting of Trading Strategy

The basic results of trading strategy before optimisation are shown in Table 2. During basic testing period, a total of 110 trades were done. It led to an increase in account of 30 065 USD. The initial value of capital was 10 000 USD when starting to apply our trading strategy based on parameters from Table 1. Final account balance reached the value of 40 065 USD on the 12th of December 2014. In particular, a total of 103 trades were profitable and only 7 ones were unprofitable. Trading strategy generated 63 signals to enter a long position and 47 signals to enter a short position. We left a position on the basis of profit target 63 times, and only 6 times on the basis of predetermined value of stop loss. The probability that a trade will not bring a loss reached 93.64%. Effectiveness that is represented by the ratio of profit after deducting losses and total profit reached 94.84%. When entering a short position, the probability that strategy will not bring a loss increased to 97.87%. On the other hand, when entering a long position, the probability fell to 90.48%. In general, overall characteristics of trading strategy are very positive. However, there is still space for improvements.

Tab. 2: Basic results of trading strategy before optimisation

Initial Account in USD	10 000	Losing Trades	7
Net Capital in USD	40 065	Efficiency in %	94.84
Number of Trades	110	Profitability in %	93.64
Profitable Trades	103	Rate of Growth in %	300.20

Source: Habudová (2015), modified by author

It is important to answer two principal questions before further modifications and optimization of any trading strategy:

a) Is the value of profit target set optimally for particular market and given trading strategy? If we leave a position too early or the profit target is unattainable, then any possible profits may be unnecessarily reduced.

b) It is absolutely essential for any steadily profitable trading strategy whether we risk adequate amount of money per contract for particular market and trading strategy. This question is how to set a value of stop loss properly.

When applying the value of MFE, which delivers us information about the maximum amount of profit that could be achieved, it is possible to analyse a success rate of trading strategy using different values of profit target. As it has already mentioned in this chapter, we left a position on the basis of profit target 63 times. This number corresponds to tick volume of 80. The corresponding profit is 24 570 USD. Simulated values of profit for the tick volume between 50-140 and respective numbers of trades are shown in Table 3. Best results were achieved when tick volume reached the value of 60. At this value we left a position 94 times on the basis of profit target. The overall profit reached the value of 27 260 USD, which is about 2 690 USD higher than in default value of tick volume that was 80. One can observe that we achieved better results also for tick volume of 70. When the number of trades is 74, we achieved profit of 25 160 USD. Profit drops gradually when the value of tick volume is higher than 80.

Tab. 3: Simulated values of profit for different tick volume

Tick Volume	50	60	70	80	90	100	110	120	130	140
Number of Trades	97	94	74	63	50	43	40	36	27	22
Profit in USD	23 280	27 260	25 160	24 570	22 000	21 070	21 600	21 240	17 280	15 180

Source: Habudová (2015), modified by author

As already stated in Introduction section of this paper our aim is backtesting of trading strategy in futures market and its optimisation using management of normalized risk and amount of contracts per trade assuming unvarying other parameters of trading strategy. In other words, our intention is to compare consistently optimized strategy with original trading strategy before its optimisation as shown in Table 2.

5 Optimisation of Trading Strategy by Nonlinear Conditional Volatility Model

In Chapter 3, we estimated volatility using EGARCH(1,1) model. These estimations will be applied to optimize our trading strategy in futures market. For the purpose of this paper, volatility estimations will be divided into 4 intervals. We assigned a value of stop loss to each interval and determined number of contracts per trade. Table 4 presents all subintervals and corresponding number of contracts. The value of stop loss is always based on estimation of volatility from previous day. For example, if the value of volatility estimated by EGARCH(1,1) model at time t-1 is equal to 0.00003, then at time t we open a position with tick volume (stop loss) of 16.7 and 3 contracts.

Tab. 4: Values of stop loss and number of contracts for volatility intervals

	Value of Stop Loss (Tick Volume)	Number of Contracts
(0,00000 – 0,00002)	12,5	5
(0,00002 – 0,00004)	16,7	3
(0,00004 – 0,00006)	25	2
(0,00006 – ∞)	50	1

Source: Habudová (2015), modified by author

Initial trading strategy was therefore optimized by using the number of contracts per trade and on the basis of volatility as estimated by EGARCH(1,1) model while the number of intervals was reduced to 4. The results presented in Table 5 show essential characteristics of optimised trading strategy which is based on volatility as estimated by EGARCH(1,1) model. When reducing the number of intervals, the value of profit increased for optimised trading strategy significantly compared to results of initial trading strategy. It can be seen that indicators of efficiency and profitability reached lower values than before optimization. However, this fact is not redeemed by reducing a stability of optimized trading strategy.

Tab. 5: Basic results of strategy after optimisation by nonlinear conditional volatility model

Initial Account in USD	10 000	Losing Trades	24
Net Capital in USD	73 710	Efficiency in %	92.08
Number of Trades	110	Profitability in %	80.90
Profitable Trades	86	Rate of Growth in %	655.05

Source: Habudová (2015), modified by author

When summing up achieved results it can be concluded that initial trading strategy has been optimized using volatility estimates by nonlinear EGARCH(1,1) model. After optimization we have achieved much better results than in the case of initial trading strategy. This fact is evidenced by indicators like rate of growth in %, and it is also supported by the value of net capital that reached the value of 73 710 USD. Nonlinear conditional volatility model was applied for optimization of the value of stop loss and the number of positions based on subjective parameters. It is obvious that following those optimizations our profit has increased significantly comparing to initial trading strategy while maintaining favourable values of other indicators.

Conclusion

The aim of this paper was to provide backtesting and optimisation of trading strategy in futures market with a help of nonlinear conditional volatility models. Optimisations of trading strategy were carried out by management of stop loss and determination of position sizing assuming constant other parameters of trading strategy. For the purpose of this paper, we applied YM time series of the US e-mini market within time period from September 2013 to December 2014. When applying volatility estimated by nonlinear EGARCH(1,1) model the final value of account increased to 73 710 USD. Optimised trading strategy therefore delivered very positive results of profitability and efficiency.

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