Dynamic margin setting with EWMA volatilities

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Abstract: The optimal clearing margin levels are crucial for default risk management system of a clearing house. The margin levels must be conservatively high enough to provide financial protection in the default loss event, but not too high to cause market liquidity problem. A static margin setting can result in a margin level which is too high. This paper proposes a dynamic margin setting model and methodology based on value-at-risk with simulated exponentially weighted moving average (EWMA) volatilities. The EWMA model gives the largest weight to the most recent innovation, which makes the dynamic setting of the margin levels more plausible. Based on the worst-case-scenario approach, the optimal margin levels can be set by choosing the model parameters as their maximum values from across different historical periods. The back test shows that the margin setting model is not sensitive to any chosen sample period. Both optimal margin level and back test can be run on a daily basis.

Keywords: margin setting level; EWMA volatilities; default risk; derivatives.


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1 Introduction

A clearing house plays a very important role in managing default risk of derivatives trading. A clearing house has the responsibilities of settling trading accounts, clearing trades, collecting and maintaining margin monies, regulating delivery and reporting trading data. A clearing house acts as a central counterparty to all futures and options contracts by acting as a buyer to every clearing house member seller and a seller to every clearing house member buyer. Therefore, the clearing house’s critical task is to assess
and monitor any possible counterparty risks and design an effective credit risk containment system.

Margin is one of many risk management tools that are used to assess overall portfolio risk to protect traders and the market as a whole. It is particularly applied to manage market or price risks, but it is not a means to move a market one way or another. An initial margin is the margin required when the derivatives positions are initiated, while a maintenance margin is the level at which market participants must maintain their margin over time. While a trader is required to maintain a margin account with a broker, a clearing member is required to maintain a margin account known as a clearing margin with the clearing house.

The clearing margin accounts of clearing house members are adjusted for gains or losses at the end of each trading day similar to a margin account a trader must keep with the broker. However, there is no maintenance margin used for the clearing margin account that the clearing house members keep with the clearing house, so they are maintained at the original margin daily. Therefore, the clearing house members may have to add or remove the funds in their clearing margin account depending on the transaction during the day or price movements. These clearing margins can be calculated based either on gross basis or net basis. Under the gross basis, all the long and short positions of all clients are added and then entered in the records. Net basis, on the other hand, allows long and short positions to be offset against each other.

A clearing house usually applies statistical theory to determine the margin level to guard against defaults as shown in Duffie Figlewski proposed that the computation of a ‘first passage time’ probability distribution is used to analyse the degree of protection afforded by different margin levels. Gay, Hunter and Kolb suggested margins should be set at levels such that the probability of the futures price moving by an amount equal to or greater than the margin during a given time interval was constant across different commodities contracts. Warshawsky proved that margin level based on normality assumption will be under-estimated. Based on the paradigm of efficient contract design proposed by Brennan. Fenn and Kupiec developed alternative models of an efficient prudential margin management policy. Longin (1999, 2000) and Cotter (2001) adopted an extreme value theory to determine the appropriate margin levels.

In all of these proposed methodology margin settings, the optimal margin level should be determined by weighing between cost and benefit tradeoffs. A high level of margin can provide a better financial safeguard against a small default probability. An extreme theory proposed by Longin can provide a solution to margin setting which is high enough to protect a small probability of a large price movement. Although a default is likely to occur when there is a large price movement with a small probability around the tail of the distribution, it is difficult to make an appropriate judgment on how small that default probability should be for deriving an optimal margin level. Moreover, the smaller probability, as we move further out in the distribution tail, would result in a higher level of margin, which is costly to clearing house members and traders.

The main concern that initial margin should be set high enough to protect traders in the event of potential default around the tail of the distribution is remarkably important only if the initial margin level is set in a static manner. Given that clearing margin accounts and margin accounts are settled daily, optimal margin levels should be dynamically considered to give a clearing house an appropriate approach to balance between opportunity costs and prudential concerns. This paper proposes a methodology
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to set a dynamic optimal margin levels that reflect the latest market volatilities based on exponentially weighted moving average (EWMA) volatilities.

This paper is organised as follows. Section 2 discusses margin setting philosophy. In Section 3, margin setting model based on value-at-risk and EWMA volatilities is explained. Back testing of a proposed model is considered in Section 4. Section 5 contains a discussion and conclusion.

2 Margin setting philosophy

There are two approaches for a clearing house to set margins. One approach is to set them sufficiently high to cover all possible volatility environments, but not often change them. This is considered a static approach. The other way is a dynamic approach in which margins are set to reflect changes in market volatility in a timely manner. That is, margins are set lower in less volatile periods and higher in more volatile periods. Thus, margins are often changed when the volatility environment experiences a sustained change. When daily price moves become more volatile, margins are raised to account for the increased risk. Similarly, when daily price moves become less volatile, margins are lowered because the risk of the position also decreases. This is the margin setting philosophy adopted by the CME Clearing and the Thai Clearing House (TCH).

Given strong evidence that the distribution of futures price change has a fatter tail than that of the normal distribution, a margin level set by normality assumption will be underestimated. Kofman11 (1993) introduced a non-parametric model called a tail index representing the weight of the distribution tail to set appropriate margin levels for futures contracts. Arguing that empirical distribution is difficult to handle, Longin12 proposed that the margin levels are set by an extreme value theory. An extreme value theory can provide a better prediction of default probability around the tail of the distribution. Since the margin levels are not often adjusted under a static approach, an extreme value theory is a better method compared to a value-at-risk method since it can provide a margin level. Longin13 proposed the margin level set by an extreme value theory by arguing that an extreme movement or a large price variation are central to the margin-setting problem. He showed that using normality assumption leads to dramatic underestimates of the margin levels due to the insignificant weight of the tails of the normal distribution. In his paper, the optimal margin level for a given probability of margin violation is computed using the distribution of extreme price changes.

Another way to set the appropriate margin level is by a dynamic approach under which the margin levels are not as high as the ones set by a static approach but often adjusted to reflect latest price volatilities. Although high margin levels can provide better financial protection in the default loss event, too high margin levels can have a negative impact on the futures market in several ways. High margin levels increased transaction costs to the investors and can lead to lower market liquidity and market depth. Therefore, setting an optimal margin level by balancing between default risk and market liquidity is the main task of a clearing house.

Even though a potential default occurs when there is a large futures price change, there is a maintenance margin which acts as an early warning signal before the investors’ margin account balance is wiped out. The investors are required to deposit additional funds when their margin account balance falls below a maintenance margin level. For
clearing margin account, there is no such maintenance margin, but the clearing house members are required to maintain the original initial margin level at all time. Thus, they may be required to put up additional funds at the end of the day and even intraday if needed. This means that the clearing house members would have to deposit additional funds on a daily basis even when there is small price change that adversely impacts their futures positions. As a result, the high level of margin under a static approach would impose too high initial cost to the clearing house members and may not be an optimal solution for clearing margin level setting.

Moreover, clearing house members are also required to make a clearing contribution to the clearing funds. This clearing fund is designed to protect the market participants including the clearing house in the event of abnormal market condition or extreme price change. In other words, the clearing margin amount provides a financial protection under the normal market condition and the clearing fund amount is used when there is an extreme event. Therefore, setting clearing margin level with value-at-risk method would be more appropriate than with extreme value theory because value-at-risk method can provide a clearing margin levels for a given probability of margin violation under normal market condition. However, to maintain low probability of margin violation, such margin levels must often be adjusted to reflect the latest price volatilities, which will result in a dynamic margin setting. This paper proposed a value-at-risk method with simulated EWMA volatilities to set the dynamic optimal margin levels. This will result in a margin level which is high during high price volatility and vice versa.

### 3 Margin setting with VaR and EWMA volatilities

The optimal margin level can be set by the following value-at-risk with high enough confidence level, $\alpha$.

$$\text{Var} = \mu \pm Z_{\alpha} \sigma$$

Equation (1) is value-at-risk measure with normal distribution assumption, where $\mu$ is the expected rate of return of the underlying asset, $Z$ is the Z-score from a standard normal distribution with $\alpha\%$ confidence level, and $\sigma$ is the standard deviation of underlying asset return.

To make sure that optimal margin levels will be large enough to protect the clearing house from incurring the loss in the default event, the risk parameters in equation (1) should be estimated under the worst-case scenario approach. That is, $\mu$ and $\sigma$ in equation (1) are derived by choosing their maximum values from different historical periods like 20, 60, 120, and 250 days.

The underlying asset price movements can be viewed as drawn from a normal distribution with time-varying parameters. It is useful only if this time variation has some predictability. Generalised autoregressive conditional heteroskedastic (GARCH) was developed by Engle and Bollerslev. They assume that the asset return at time $t$ has a normal distribution, conditional on parameters $\mu_t$ and $\sigma_t$. That is, $r_t \sim \Phi(\mu_t, \sigma_t)$. GARCH model assumes that the conditional variance depends on the long run average variance, the latest innovation, and on the previous conditional variance.
Define $h_t = \sigma_t^2$ as the conditional variance, using information up time $t-1$, and $r_{t-1}$ as the previous day return. GARCH (1,1) process can be written as

$$h_t = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta h_{t-1}$$  \hspace{1cm} (2)$$

EWMA is the special case of the GARCH process, where $\alpha_0$ is set to zero, and $\alpha_1 + \beta = 1$. Asset return volatilities can be modelled using the following EWMA forecast, which is a weighted average of the previous forecast.

$$\sigma_{t+1|t} = \sqrt{\lambda \sigma_{t+1|t-1}^2 + (1-\lambda)r_{t+1}^2}$$  \hspace{1cm} (3)$$

The forecast $\sigma_{t+1|t}$ is the weighted average of the previous forecast with the weight $\lambda$, and the latest squared innovation, with the weight $(1-\lambda)$. $\lambda$ is called the decay factor, determines the relative weights placed on previous observations and $0 < \lambda < 1$. The weights $\lambda$ decrease at geometric rate. The lower $\lambda$, the more quickly older observations are forgotten.

Both GARCH and EWMA models place more weight on latest innovation and both employ exponentially smoothing. Over a one-day horizon, the two models are quite similar and often indistinguishable from each other. However, the longer term extrapolation from the GARCH and EWMA models may give quite different forecasts. The main difference between GARCH(1,1) and EWMA is that GARCH(1,1) model includes the mean reversion term. Generally, variance tends to be mean reverting to a long run average value. However, if the estimation of $\alpha_1 + \beta$ in equation (2) turns out greater than one, which is the case with our data, GARCH(1,1) model is unstable for our data set and EWMA model is preferred, according to Hull (2014)\textsuperscript{16}.

From equation (3), if we let the forecast error ($\epsilon_{t+1|t}$) equal to zero represented by equation (4), the decay factor $\lambda$ can then be calculated based on equation (4) by minimising the variance of this forecast error, called root mean squared error (RMSE) in equation (5).

$$E_t[\epsilon_{t+1|t}] = E_t[r_{t+1}^2] - \sigma_{t+1|t}^2 = 0$$  \hspace{1cm} (4)$$

$$RMSE = \left[\frac{1}{T} \sum_{t=1}^{T} \left(r_{t+1}^2 - \sigma_{t+1|t}^2(\lambda)\right)^2\right]^{1/2}$$  \hspace{1cm} (5)$$

<table>
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<tr>
<th>Return\textsuperscript{2}</th>
<th>20 days</th>
<th>60 days</th>
<th>90 days</th>
<th>120 days</th>
<th>250 days</th>
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<tr>
<td>Sum of squared error</td>
<td>0.14046198%</td>
<td>0.14037962%</td>
<td>0.13985120%</td>
<td>0.13980931%</td>
<td>0.10731670%</td>
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<tr>
<td>RMSE</td>
<td>0.001409515</td>
<td>0.001428426</td>
<td>0.001469081</td>
<td>0.001451982</td>
<td>0.001530738</td>
</tr>
<tr>
<td>Optimal decay factor</td>
<td>0.882666402</td>
<td>0.882723183</td>
<td>0.882573228</td>
<td>0.882634318</td>
<td>0.872588404</td>
</tr>
</tbody>
</table>

\textbf{Table 1}  \hspace{1cm} DECAY FACTOR ESTIMATION FROM DIFFERENT HISTORICAL PERIODS
The SET50 index data from May 14, 2007 to March 19, 2009 are used to calculate the optimal value of the decay factor $\lambda$. Table 1 shows the results of optimal decay factor values using different $\sigma^2_{t,T-1}$ based on different historical periods of 20, 60, 90, 120, and 250 days.

The optimal value of decay factor for SET50 index data appears to be around 0.88, which is smaller than the decay factor of 0.94 used in the RiskMetrics model. This lower decay factor implies that the volatilities of SET50 index data seems to forget the older observations faster than the developed market data used to derive the optimal decay factor in the RiskMetrics model.

Even if the starting value of asset return variances, $\sigma^2_{t,T-1}$ in equation (3) is different, the asset return volatilities forecasted by EWMA will converge to the same value after a certain period of time. Figure 1 shows the comparison of SET50 index volatilities calculated by EWMA and the typical moving average volatilities calculated with equally weighted average (EWA) approach based on observations within certain historical periods; e.g., the previous 20 trading days, the previous 60 trading days. EWA volatilities with longer historical periods have smoother volatilities across time, but fail to capture volatility change in a timely manner. This is known as ghosting feature, where sudden volatility increases are abruptly incorporated into the EWA calculation and then, when the historical period passes, they are abruptly dropped from the calculation. Given this problem, the estimation of EWA volatilities will vary depending on the chosen historical periods. Consequently, the margin level set based on EWA volatilities will also sensitive to the chosen historical period.

Figure 1  Comparison of EWA and EWMA volatilities for SET50 Index (see online version for colours)

EWMA volatilities appear to quickly reflect the latest innovation in the market, especially during the high volatility period in October and November 2008. This is because EWMA volatilities can quickly adjust itself with the largest weight given to the latest information. This overcomes the aforementioned ghosting feature problem because a sudden change in volatility will immediately impact the volatility estimate and its...
influence will gradually fade as time passes. Thus, for the market that there is a possibility of a volatility shock, the EWMA model can provide a better volatility estimate for setting optimal margin levels. As a result, such optimal margin levels should be dynamically reviewed and changed to reflect the latest innovation too.

4 Back testing

The dynamic margin levels can be set by equation (1) with volatilities simulated by EWMA model explained in the previous section. To avoid the model risk and to make sure that the model and methodology employed in setting optimal margin levels meet the requirements they were intended, margin setting model must be back tested by comparing them with the actual price movements of clearing members’ futures positions calculated on the margin date using actual market price.

With a 99% confidence level, there is a 1% chance the actual price movements of clearing members’ futures positions will be over the optimal margin level by the end of the day under normal market conditions. At the end of the day, if the actual price movement of clearing members’ futures positions is greater than the optimal margin level, then we might conclude that the margin level has been violated and such event is called margin violation. If there have been too many margin violations, then the margin setting model may not be adequate for the futures price movement.

The back test for a proposed dynamic margin setting model should be run on a daily basis by comparing such dynamic optimal margin level with the actual price movements of clearing members’ futures positions. At 99% confidence level, there should theoretically be one violation over a window of 100 trading days. On the contrary, if the actual price movement of clearing members’ futures positions is lower than the optimal margin level, then the chosen margin setting model and methodology can be considered appropriate and accurate in predicting the potential loss exposure for that particular futures contract.
Figures 2 to 5 show such back tests for different chosen historical periods, in which both margin levels and actual value-at-risk measure are estimated based on data of previous 60, 90, 120, and 250 days. This is to guarantee that the margin setting model will not be sensitive to any chosen sample period.

**Figure 3** Back test of margin setting model with 90-day historical data (see online version for colours)

![Graph showing back test results with 90-day historical data](image-url)

**Figure 4** Back test of margin setting model with 120-day historical data (see online version for colours)

![Graph showing back test results with 120-day historical data](image-url)

The back test results of margin setting model show that the optimal margin levels are not sensitive to different chosen sample period, but the margin levels seem to be in line with the actual price movements of clearing members’ futures positions much better when the calculation is based on shorter historical period. This is due to the fact that EWMA model assigns more weights to the most recent data.
5 Conclusions

Every clearing house has an important task of setting reasonably conservative clearing margin levels to provide a primary financial protection in the default loss event. Clearing margin requirement should be risk-based with its setting model and methodology customised for different underlying assets. Depending on its policy, each clearing house can set the clearing margin level either as static or dynamic. Because of its static nature, the static margin must be set high enough to cover potential default loss until the next review date. The extreme value theory can provide high enough margin level that can sustain large futures price change even at the low probability of occurrence around the distribution tail. However, too high margin levels may lead to market liquidity problem because clearing house member and its investors must bear high transaction costs.

Reasonably conservative margin levels which are not too low and not too high should be set to provide financial buffer in the default loss event under normal market conditions while the clearing fund is designed as an additional financial protection during an extreme event or large price change. Since value-at-risk is measured under normal market assumption, this paper proposes that the clearing margin should be set using value-at-risk model with simulated EWMA volatilities. Using the worst-case-scenario approach, the parameters in margin setting model are chosen as their maximum values estimated from different historical periods. EWMA model places more weight on the most recent information, which makes the setting of risk-based clearing margin levels more plausible. That is, the clearing margin can be changed dynamically to reflect the most recent market risk level.

The back tests of margin setting model and methodology show that the margin results are not sensitive to any chosen historical period. Both margin levels and back test can be run on a daily basis, but it depends on each clearing house’s policy on how often the margin should be changed.
Notes

10. Longin, Supra, at note 7.
12. Longin, Supra, at note 7.