and 99.5% respectively. Finally, its results are compared with historical simulations (HS) and normal methods (see Table 5).

Table 5
Different Confidence Horizontal Portfolio VaR

Confidence	HS	Norm	GARCH-EVT-COPULA
95%	2.585%	2.570%	5.759%
99%	5.220%	3.635%	8.630%
99.5%	6.080%	4.025%	9.370%

From Table 5 we can know that:

(a) The VaR calculated by Norm is the minimum at each confidence level. The VaR calculated by Norm method is the minimum under each confidence, it underestimates VaR, which is less likely to underestimate the actual risk, which underestimates the VaR, which is less likely to underestimate the actual risk.

(b) When the confidence level from 95% to 99.5%, VaR change is the largest HS method, the smallest change is the GARCH-EVT-COPULA method. This result shows that with the increase of confidence, VaR estimated by HS method is susceptible to extreme value and poor stability. However, the VaR of the GARCH-EVT-COPULA model is small and the stability is good.

(c) At different confidence levels, the VaR calculated by GARCH-EVT-COPULA is significantly larger than the other two methods. In particular, at 99% confidence, HS and Norm calculated VaR of 5.220% and 3.635%, respectively, much less than 8.630% calculated by GARCH-EVT-COPULA. This result indicates that there is a risk of serious underestimation of the black swan incident.

(d) The VaR and the fluctuation values based on

the GARCH-EVT-COPULA model are more reasonable to estimate the VaR reasonably, whether it is at different confidence levels or when the confidence changes. The above model needs to be further determined by returning the inspection link to meet the requirements.

5.7 Return Test

In order to evaluate the effect of the model, we use the 2185 group of data (January 9th, 2008 to December 30th, 2016) to predict the VaR of structured financial products portfolio in Really Treasure Platform and do a Kupiec test. The Kupiec test is also called the LR Likelihood Test, whose basic idea is to assume that the actual survey days are N0 and the number of failures is n, then the failure rate is $p = n / N0$. Let VaR be the confidence level $p*$. Assuming that the VaR estimate has time independence, the number of failed days n follows the binomial distribution with parameters N0 and p, that is $n \sim B(N0, p)$. Under the null hypothesis $p = p*$, likelihood ratio is $LR = -2\ln[(1-p*)N0-n(p*)n+2\ln[(1-n/N0)N0-n(n/N0)n \sim \chi 2(1)$. Under a significant level of 5%, if $LR > 3.8415$, it rejects this model. We further test the model, we predict the VaR of the data within the based on the GARCH-EVT-Copula model sample in the five kinds of reliability. According to the Breakdown Ratio (VR),we get the rule: If VaR$\in$ ［0.8, 1.2］, this model predicts the VaR is appropriate. We have come up with 250 days (about a year) failed days, failure rate, the results show that the probability of failure in the green area, that model is applicable (see Table 6).

Table 6
Return Test (Time Window W = 250)

Model	Theoretical number of breakthroughs	Actual number of breakthroughs
HS	2.5	2
NORM	2.5	2
GARCH-EVT-COPULA	2.5	2

Table 7
Return Test (Time Window W = 2163, Whole Samples)

Models	Theoretical number of breakthroughs	Actual number of breakthroughs	Breakthrough ratio
HS	16.1	19	1.180
NORM	16.1	13	0.807
GARCH-EVT-COPULA	16.1	15	0.932

CONCLUSION

At present, most scholars use the historical simulation method, the normal method and the Monte Carlo method to measure the market risk VaR. However, these three traditional methods have great limitations in measuring the market risk of structured financial products under the Internet financial environment. In the

Internet financial environment, financial products have a wide range of spillover and rapid infectious. Under the current international market, "Black Swan" event frequent. Therefore, the risk of control is more and more important to prevent small probability events, while the traditional distribution of assumptions in the traditional method and the handling of extreme events have great limitations.

Hence, based on the perspective of investor risk management, this paper introduces the EVT model and COPULA model, which are different from the traditional financial products in the financial environment. We use the EVT model to capture the tail features and COPULA function of the excellent modeling because of the excellent characteristics, and use GARCH-EVT-COPULA model to construct the GARCH-EVT-Gaussian-COPULA and GARCH-EVT-t-COPULA methods. We take the Really Treasure Platform for example, and measure the risk of equal weight portfolio of linked stock and optimize the innovative VaR measurement method. Firstly, the generalized Pareto distribution is used to calculate the marginal distribution of the new message sequence, and the joint function is obtained by substituting the Copula function. In addition, the Monte Carlo method is used to estimate the VaR of the equal weight portfolio. Secondly, the VaR of the three methods is compared and do a return test using these three methods, including History Simulation method (HS), Normal method (Normal) (traditional methods) and GARCH-EVT-COPULA model.

From the result of VaR test comparison using these three methods, we can conclude: (a) Three methods for the time window to return the number of breakthroughs in the green area, can meet the basic requirements of risk measurement. (b) In these three methods, the VaR calculated by GARCH-EVT-COPULA is significantly larger than the other two methods under different confidence levels. For instance, under the 99% confidence level, HS and Normal method calculated VaR in 5.220% and 3.635%, respectively, much less than GARCH-EVT-COPULA calculated 8.630%, which shows that GARCH-EVT-COPULA is better able to portray the extreme risk and it can accurately measure the risk under the current black swan event frequent stage. In the Internet financial environment, this study will help investors clear the risk degree of product, and choose their own structured financial products.

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