Integrating GJR-GARCH and LightGBM Quantile Regression Model Based on Gating Mechanism

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Abstract. In the financial field, accurate prediction of price changes and risks is an important reference for making decisions and now the combination of machine learning and statistical models has shown advantages. This study combines dynamic regulation based on market environmental factors with the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity model (GJR-GARCH) modified by Cornish Fisher expansion and the Light Gradient Boosting Machine (LightGBM) quantile regression machine learning model to capture extreme market risks and construct conditional probability distribution. The experimental results indicate that the hybrid model proposed in this study can effectively capture market risks and improve prediction accuracy, especially in enhancing the prediction accuracy and calibration quality of tail risk (VaR). Solving the problem of traditional models usually using linear autoregressive structures and machine learning facing sparse sample prediction failures, while avoiding the black box effect of deep learning. The result shows that the CRPS value is the lowest in JPM with 0.2148, compared with other models, and it has shown robust performance on representative stocks in different industries with CRPS value between 0.17 to 0.27, proving that the model has good generalization ability.

Keywords: GJR-GARCH Model, LightGBM Quantile Regression, Gating Mechanism Fusion, Cornish Fisher Expansion, Conditional Probability Distribution.

1 Introduction

In the financial industry, accurate modeling and estimation of asset price changes and their associated risks are the cornerstone of decision-making for investors, portfolio managers, and risk analysts [1]. In recent years, machine learning methods or using neural network have provided more powerful computational frameworks for financial data models and risk prediction [2][3].

In 1993, Lawrece et al. revised the GARCH-M model based on this, pioneering the inclusion of seasonal effects, asymmetric shocks, and nominal interest rates simultaneously, known as the GJR-GARCH model [4]. The fusion of machine learning methods and traditional statistical models has become a new trend and has been proven to have better prediction and estimation accuracy. Jakub Michańków et al. and Hu et al. syste

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matically integrated various variations of GARCH models with deep learning methods to make them more accurate, demonstrating the advantages of integrating machine learning and statistical models [5][6]. In 2024, it was proposed to combine deep learning methods with Quantile Regression and Smooth Density Estimation to accurately estimate the complete probability distribution of financial asset returns from predicting only the direction of rise and fall. The hybrid model reduces the quantile loss to 0.1565 compared to 0.7229 for the Dense model and 0.2115 for the linear model [2]. Ke and Yin combined the traditional CAViaR framework with machine learning algorithms to construct a multi-dimensional and multi-layer CAViaR model, which was optimized using gradient descent and genetic algorithm, reducing the model loss to 0.10 and 0.04 respectively [7]. The above research provides inspiration for this study to explore how to construct intelligent agents that are not entirely self interested.

This study estimates the conditional distribution of financial asset returns and focuses on capturing extreme market risks by integrating dynamic gating mechanisms driven by market environmental factors, machine learning methods based on quantile regression and gradient boosting decision trees, and traditional statistical models such as GARCH and T-distribution.

2 Methodology

2.1 Data

The stock price data used in this study comes from the S&P 500 Stocks dataset publicly released on the Kaggle platform, which includes historical price information of the S&P 500 index from 1993 to 2020, including daily opening prices, highest prices, lowest prices, closing prices, and trading volumes of each constituent stock [8]. In addition, the S&P 500 index data has been widely adopted by academic research institutes that have published in peer-reviewed journals, covering multiple fields such as asset pricing, risk management, macroeconomic forecasting, and machine learning applications. Its data quality and reliability have formed a broad consensus in the academic community. This study selects four industry representative blue chip stocks in the S&P 500 index: Apple (AAPL), JPMorgan Chase (JPM), ExxonMobil (XOM) and Walmart (WMT) as the research object.

The preliminary statistical analysis shows that the sample asset returns show significant characteristics of fat tailedness and volatility clustering. The excess kurtosis of each sequence was significantly greater than 3, and the Jarque BERA test rejected the normality hypothesis at the 1% level. This distribution characteristic constitutes the realistic basis of this study using Cornish Fisher correction and quantile regression modeling.

2.2 Variable Selection

This study uses logarithmic return r_t as the modeling object, mainly based on its time additivity and better numerical characteristics in statistical modeling.

This study selects 9 representative market characteristics to form a vector $\mathbf{x}_t = [x_{1,t}, x_{2,t}, x_{3,t}, x_{4,t}, x_{5,t}, x_{6,t}, x_{7,t}, x_{8,t}, x_{9,t}] \in \mathbb{R}^9$, where $x_{1,t}$ represents the short-ter m realized volatility for the last 21 days:

$$x_{1,t} = \sqrt{\frac{1}{20}\sum_{i=0}^{20}(r_{t-i} - \bar{r}_{t,21})^2} \quad \bar{r}_{t,21} = \frac{1}{21}\sum_{i=0}^{20} r_{t-i} \tag{1}$$

and taking 63 trading day windows (about a quarter) to calculate the standard devia tion:

$$x_{2,t} = \sqrt{\frac{1}{62}\sum_{i=0}^{62}(r_{t-i} - \bar{r}_{t,63})^2} \quad \bar{r}_{t,63} = \frac{1}{63}\sum_{i=0}^{63} r_{t-i} \tag{2}$$

$x_{3,t}$ is the volatility term structure ratio, which is defined as the 21 day volatilit y at time t divided by the 63 day volatility during the same period. $x_{4,t}$ is the intra day log range and $x_{5,t}$ is the average of the last 5 days of intraday log range, $x_{6,t}$ is the volatility percentile rank (VIX Rank) and $x_{7,t}, x_{8,t}, x_{9,t}$ are the lagged log-returns of one day, three days and five days respectively.

2.3 Model

The model is hybrid which contains two paths. One path is the GJR-GARCH-t model driven by statistics, and the Cornish - Fisher expansion is used to modify the thick tail and asymmetry, the another path is a quantile gradient lifting regression tree driven by machine learning.

Statistic Model. For the statistical part, it uses the GJR-GARCH-t and Cornish - Fish er expansion [9]. The model aims to simultaneously characterize the volatility clusteri ng, leverage effect and non-normal residual distribution of asset returns.

Firstly, it fit the r_t by using the GJR-GARCH(1,1) to capture the leverage effect, w hich is defined as:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 I(\epsilon_{t-1} < 0) + \beta\sigma_{t-1}^2 \tag{3}$$

where ϵ_t is the residual assuming the it obey the standardized student-t distribution with the degree of freedom v, σ_t^2 is the conditional variance representing the volatility of the t-th period and I is the indicative function. The ω, α, γ and β are coefficients. T hen it calculates the sample skewness S and excess kurtosis K from the standardized r esiduals.

In order to correct heavy tailed and asymmetric, it uses 4 ordered Cornish - Fisher e xpansion to correct the standard normal quantile $z_\alpha = \Phi^{-1}(\alpha)$:

$$z_\alpha^{CF} = z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)S + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)K - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)S^2 \tag{4}$$

Ultimately, the α-quantile predicted by the statistical model is equal to the product of the conditional mean $\hat{\mu}_t$ plus the conditional standard deviation $\hat{\sigma}_t$ and the aforemen tioned Cornish Fisher corrected quantile z_α^{CF}. This part of the model systematically ca

ptures the four typical characteristics of volatility aggregation, leverage effect, fat tail, and skewness in financial return sequences. Compared with the traditional normal hy pothesis GARCH model, it improves the accuracy and feature capture of extreme qua ntile prediction.

Machine Learning. Following the gradient boosting quantile regression framework, i t chooses to use gradient boosting tree as the base learner [10][11]. For each quantile, it gets a function f(α) by minimizing the quantile loss and then converging to true con ditional quantiles. It repeats this process for each quantile α and get $f_\alpha(x_t)$.Machine le arning methods can flexibly integrate diverse information and capture complex nonlin ear patterns. Improve the performance of traditional statistical model.

Dynamic Gating Fusion Mechanism. In order to switch the weights of ML model an d statistical model under different market conditions, the gating coefficient λ_t is introd uced, which is a sigmoid monotonic function of VIX Rank $x_{6,t}$:

$$\lambda_t = \lambda_{base} + \frac{1-\lambda_{base}}{1+\exp(-k(\mathrm{VIXRank}_t-\tau))} \quad (5)$$

where the base weight for the machine learning is $\lambda_{base} = 0.3$,the gain coefficient k $= 10$ for controlling steepness and the switching threshold $\tau = 0.5$.

Overall, the α quantile predicted by the hybrid model is equal to the weighted avera ge of the machine learning prediction $f_\alpha(x_t)$ and the α-quantile predicted by the statist ical model, where the weight is the aforementioned gating coefficient λ_t. This enables the model to have adaptive market state switching capability, balancing robustness an d flexibility.

3 Results

3.1 Hybrid model on JPM

Table 1. HYBRID MODEL backtesting audit results.

Confidence	Actual Violation Rate	Kupiec P-val	Result
1.0%	0.56%	0.5130	PASS
5.0%	3.33%	0.2760	PASS
95.0%	96.67%	0.2760	PASS
99.0%	99.44%	0.5130	PASS
1.0%	0.56%	0.5130	PASS

Taking JPM as an example. Table 1 presents the main results of the HYBRID MO DEL by using Kupiec's POF test, which is used to audit the risk prediction out of sam ple of AAPL (Apple). The table provides the target violation rate, actual backtesting v iolation rate, Kupiac test P-value, and pass or fail score based on confidence levels of 1.0%, 5.0%, 95.0%, and 99.0%, respectively. As shown in Table 1, the actual penetrat

ion rate of the value at risk (VaR) coverage of the model at the confidence levels of 1. 0% and 5.0% is close to the target value. Kupiec P values were far greater than the sig nificance level of 0.05, and all passed the audit. This shows that when the model is use d to predict the extreme risk and normal fluctuation of AAPL assets, the prediction int erval is highly consistent with the actual distribution and accurately depicts the fat tail feature.

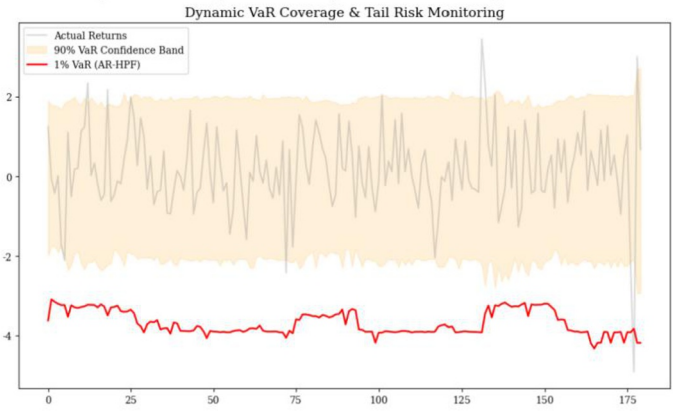


Fig. 1. Actual observations and predicted values at different confidence levels (Photo/Picture c redit: Original).

Fig. 1 shows the comparison between the predicted value and the actual value. The bla ck solid line in Fig. 1 represents the actual closing price, and the colored shaded area r epresents the prediction interval of the model at the 90%var confidence level. It can be seen that the model changes with market fluctuations. When the market fluctuates vio lently, the prediction range widens, and when the market is calm, the range narrows. O nly a few points broke through the prediction interval of the model under 1% var. It sh ows that the model can dynamically capture the conditional heteroscedasticity of data.

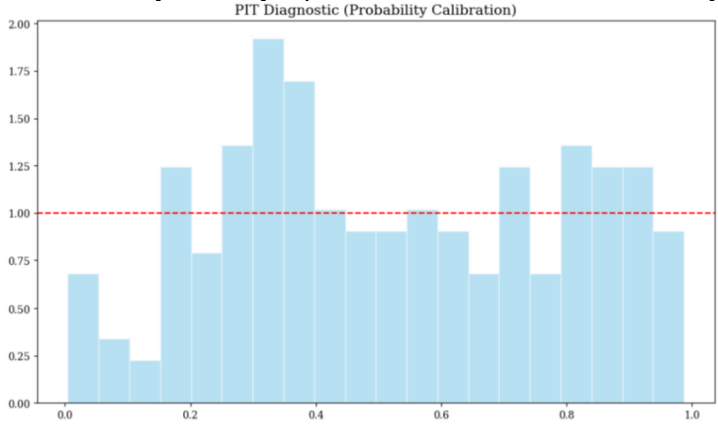


Fig. 2. Comparative analysis of pinball loss under different quantiles (Photo/Picture credit: Ori ginal).

Fig. 2 histogram shows a relatively flat distribution as a whole, and each square colum n is close to the red dotted line, indicating that the model is well calibrated on the test set. There is no obvious accumulation at both ends of the graph, which shows that the model effectively modifies the peak and thick tail characteristics of the data, and allev iates the problem of failure of the traditional model in extreme market conditions.

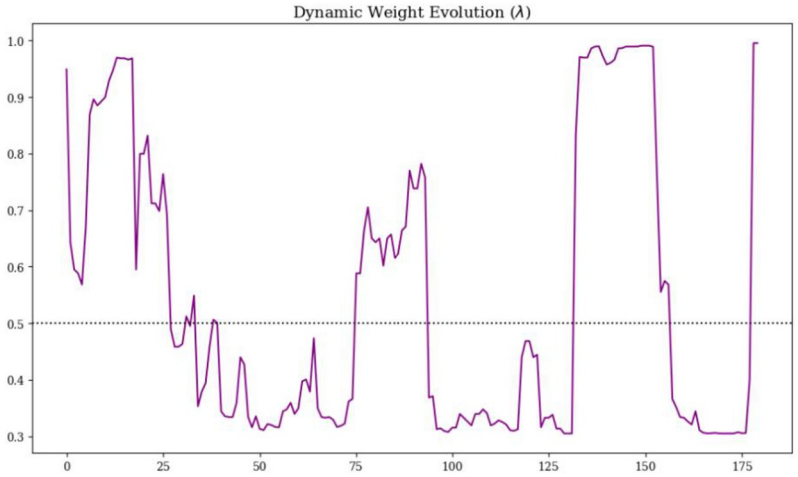


Fig. 3. Variation diagram of mixing proportion coefficient λ with time (Photo/Picture credit: Original).

Fig. 3 shows that the dynamic coefficient will change with time, showing that the mod el captures the changing characteristics of the data, so that the coefficient can be dyna mically adjusted, showing the effectiveness of the model.

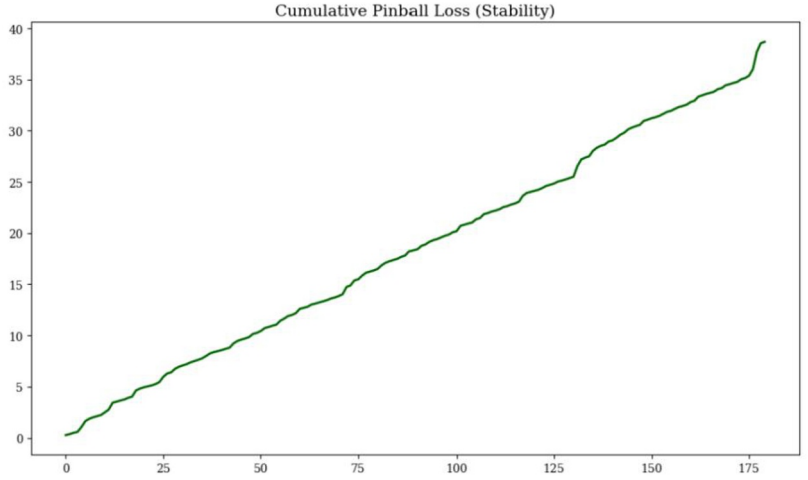


Fig. 4. Cumulative pinball loss of the model over time (Photo/Picture credit: Original).

Fig. 4 shows that the cumulative Pinball loss shows a relatively stable linear growth o ver time. On the whole, there is no sudden slope step in the curve, which indicates that the model is stable throughout the back test period, and there is no serious prediction collapse due to specific market shocks.

3.2 Comparison with Different Models

It compares the Hybrid model with four benchmark models: a constant Gaussian basel ine (Static Normal), a pure quantile GARCH model without Cornish - Fisher expansio n correction(QF-GARCH), a classic statistical volatility model combined with t distrib ution(Pure GARCH-T), and a pure machine learning approach (Vanilla-LGBM).

Table 2. Comparative performance.

Model	CRPS	VaR_1%_Hit	VaR_5%_Hit
Static Normal	0.221774	0.005556	0.016667
QF-GARCH	0.228485	0.005556	0.005556
Pure GARCH-T	0.215093	0.005556	0.016667
Vanilla-LGBM	0.215325	0.005556	0.033333
Hybrid model	0.214815	0.005556	0.033333

From Table 2, it can be seen that the hybrid model achieved the lowest CRPS valu e. The performance of QF-GARCH is the worst, followed by Static, which indicates t hat the model cannot adapt to the characteristics of financial data changing over time a nd cannot capture the fat tails and asymmetry of financial data without non-linear capt ure of environmental factors and simple assumption of normal distribution. Secondly, Vanilla-LGBM is slightly lower than the GARCH model combined with t-distribution, indicating that capturing conditional variance in simple machine learning models with out statistical dynamics constraints may not be as good as classical GARCH models. P ure CARCH-T is slightly better than QF-GARCH, indicating the effectiveness of Cor nish Fisher expansion correction and T-distribution.

In terms of tail risk capture, all models have consistent exposure rates at 1% VaR, with slight conservatism and sufficient safety margin. At a VaR of 5%, QF-GARCH i s the most conservative (with a contact rate of only 0.0056), while Static Normal and Pure GARCH-T are also overly conservative (both 0.0167). The contact rate of the hy brid model is about 2.2%, which is still conservative but significantly better than tradit ional statistical models and QF-GARCH. This indicates that the introduction of machi ne learning can effectively alleviate the overly conservative bias of traditional models, while maintaining safety and being closer to the real risk distribution, reflecting better adaptability.

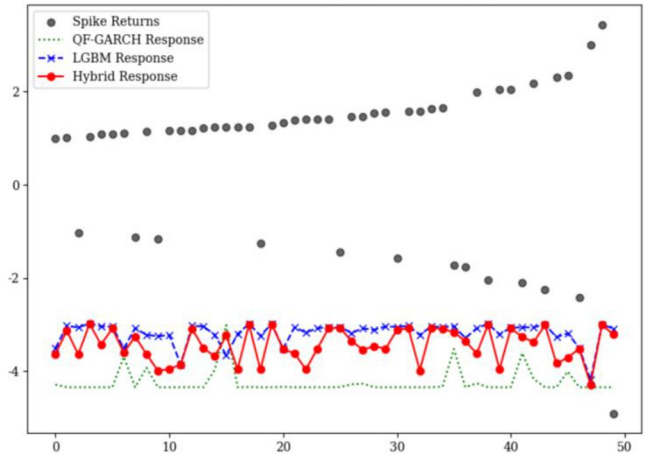


Fig. 5. Model response during high volatility spikes (Photo/Picture credit: Original).

Focusing on the volatility spikes, from the Fig. 5, the Hybrid model (red) exhibits a si gnificantly more proactive and deep-seated response compared to the Vanilla LGBM (blue). There are three larger peaks in Fig. 5, the depth of the red line detected downw ard is much deeper than the blue line. It shows that the hybrid model is safer to predict under greater impact with Cornish Fisher correction. While the pure ML approach i.e LGBM often suffers from response lately during sudden market shocks, the integratio n of GARCH-based dynamics allows the Hybrid model to adjust its risk boundaries in stantaneously. In addition, compared with the QF-GARCH (green dotted line), althou gh QF-GARCH sets a rigid risk bottom line and cannot track the market recovery, the hybrid model will adjust with the changes of the market and dynamically recalibrate, s howing better adaptability.

3.3 Hybrid Model Application

In order to verify the robustness and generalization ability of the hybrid model in diffe rent market environments, it selected representative stocks from four different industri es: AAPL (Technology), JPM (Finance), XOM (energy) and AMZN (retail) for back t est audit, and the results are shown in Table 3.

Table 3. Generalization performance evaluation of representative stocks in different industries

STOCK	CRPS	VaR_1%_Hit
AAPL	0.263861	0.011111
JPM	0.214815	0.005556
XOM	0.176749	0.011111
WMT	0.233167	0.005556

The CRPS index remains at a low level (0.17-0.27) in all stocks, indicating that t he model can accurately capture the probability distribution of assets with different pr

operties and is universal. And in terms of the 1% var touch rate (index), the results of all test assets are little higher than or lower than the theoretical threshold of 1%. Amon g them, AAPL and XOM's touch rate (1.11%) is very close to the theoretical target, w hile other stocks' performance is slightly cautious with an average of about 0.56%. Th e results show that the model is not only over fitting for specific data, but also shows a pplicability on assets with a variety of volatility characteristics, and can predict extrem e market risks across industries.

4 Discussion

The quantile regression in this study requires separate regression calculations for each quantile, which is inefficient and limits accuracy. Wang et.al proposed the Generative Quantile Regression method, which does not require separate regression for each qua ntile, but can output the complete conditional distribution at once [12]. In the future, t his Generative Quantile Regression can be used in conjunction with machine learning methods to improve efficiency and accuracy. At present, the gating mechanism in this study is based on manually set empirical formulas and only relies on vixrank parame ters. This mechanism may not be able to perfectly adapt to the extreme and complex no nlinear state transitions in financial markets. In the future, it can refer to the Garchnet framework proposed by Buczynski & Chlebus and improve it by using neural network s to autonomously learn and fuse weights and parameters [3]. In addition, the feature v ectors in this article mostly rely on traditional features. In the future, it can refer to K e & Yin to introduce multidimensional features, such as financial news sentiment indica tors extracted by large language models, social media panic indices, etc., to more sens itively capture market sentiment features [7].

5 Conclusion

To sum up, the paper studied how to use machine learning and traditional statistical m odels to capture extreme market risks by introducing dynamic gating mechanism base d on market environmental factors and constructing conditional probability distributio n. The model combines the advantages of the two, pays attention to the factors of the market itself, and uses environmental factors such as volatility to describe the signific ant spikes, thick tails and asymmetries in the financial time series. By fully combining the advantages of the two methods, the prediction accuracy is improved and during pe riods of intense volatility, the hybrid model demonstrates greater agility and foresight, compared with the traditional statistical model or machine learning method, providin g a more substantial safety margin. In the audit of 1% var penetration rate, it performe d well in different industry data, demonstrating the ability to capture positive tail risks.

Although the model proposed in this article has demonstrated good risk prediction ability in backtesting, the dynamic complexity of financial markets provides a broader exploration space for subsequent research. The current machine learning path mainly relies on LightGBM, in the future, generative AI can be introduced to monitor and lea rn more indicators and features. Through these models, it is expected to further impro

ve the accuracy of tail risk capture and achieve an improvement from quantile regressi on to full probability density generation. Secondly, current feature engineering is main ly based on quantity data. Future work can continue to explore incorporating unstructu red data, such as news sentiment analysis, social media sentiment indices, and macroe conomic leading indicators, into feature matrices. By combining Generative AI to capt ure non-traditional risk factors, the model will be able to more sensitively perceive ma rket sentiment reversals driven by policy changes or unexpected events. In addition, th e current focus of this study is on measuring the risk of individual assets. In the future, the focus can shift to multi asset risk modeling, using graph neural networks (GNNs) to explore the dynamic correlations between assets. This will help improve the applica bility of the predicted results.

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