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Modeling Financial Asset Returns and Initial Risk Exploration under the Gaussian Assumption

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Abstract. The Gaussian distribution assumption has long been a cornerstone of financial theory and risk management due to its mathematical tractability. However, its applicability to real-world asset returns, particularly in emerging markets, remains a critical empirical question. This study empirically investigates the validity of this assumption for modeling returns and measuring risk in the Chinese A-share market. Utilizing a dataset of 50 manufacturing stocks from 2010 to 2019, people employ descriptive statistics, formal normality tests (Jarque-Bera, Kolmogorov-Smirnov), and visual diagnostics (Q-Q plots) to analyze distributional properties. Maximum Likelihood Estimation (MLE) is employed to estimate the parameters of a Gaussian distribution, and a parametric Gaussian Value-at-Risk (VaR) model is constructed. Our findings robustly indicate that returns exhibit significant leptokurtosis and negative skewness, deviating substantially from normality. Consequently, the Gaussian-based VaR model systematically underestimates tail risk, as evidenced by a violation ratio of 1.42 at the 99% confidence level during backtesting. Finally, it would be valuable to extend this study to other emerging markets. Comparing the results across different markets can help us understand whether the deviation from normality is a common phenomenon in emerging economies or specific to the Chinese A-share market. This cross-market analysis can provide broader insights into the applicability of the Gaussian assumption in global financial risk management.

Keywords: Gaussian Distribution, Financial Risk Management, Maximum Likelihood Estimation (MLE)

1. Introduction

The relentless pursuit of understanding and managing financial risk stands as a cornerstone of modern finance. At the heart of this endeavor lies the critical task of modeling the seemingly unpredictable movements of asset prices–their returns. For decades, the Gaussian, or Normal, distribution has served as a foundational pillar upon which numerous financial theories and practical risk management tools have been built. Its mathematical tractability, governed by the Central Limit Theorem under assumptions of independent and identically distributed random variables, offered an elegant framework for representing market uncertainties. Consequently, the assumption that asset returns follow a Gaussian distribution became deeply ingrained in both academic finance and

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industry practice, underpinning models for option pricing, portfolio optimization, and, crucially, quantitative risk measurement.

However, the elegant symmetry and thin tails of the Gaussian bell curve often stand in stark contrast to the turbulent reality of financial markets. This disconnect between the assumed model and empirical reality poses a significant problem. Risk management, particularly the quantification of potential losses, relies fundamentally on accurately capturing the probabilities of adverse events. If the underlying model underestimates the likelihood of extreme outcomes, risk measures derived from it will be inherently flawed, potentially leading to catastrophic underestimations of true risk exposure.

This thesis directly confronts this critical issue by undertaking an empirical investigation titled "Modeling Financial Asset Returns and Initial Risk Exploration under the Gaussian Assumption." Our primary objective is twofold: first, to rigorously examine the validity of the Gaussian assumption by analyzing the empirical distribution of returns for selected financial assets; and second, to explore the practical consequences of this assumption, specifically its impact on a cornerstone risk measure–Value-at-Risk (VaR). People focus on applying fundamental statistical concepts: they model returns assuming normality, utilize Maximum Likelihood Estimation (MLE)-the workhorse method for fitting distribution parameters under this assumption – to estimate mean returns and volatilities, and subsequently compute parametric Gaussian VaR. VaR, defined as the maximum potential loss over a specific time horizon at a given confidence level (e.g., 95%or 99%), is a ubiquitous regulatory and internal risk metric. By calculating VaR under the Gaussian assumption and comparing it with the observed empirical distribution (particularly the tails), researchers aim to quantify the potential underestimation of risk inherent in this widely used yet potentially flawed approach.

Motivation for this research stems from its profound practical implications. Financial institutions, investment funds, and regulators globally rely on VaR and related models for capital adequacy requirements, setting trading limits, and strategic asset allocation. Underestimating risk due to an inappropriate distributional assumption can lead to insufficient capital buffers, inadequate hedging, and ultimately, vulnerability to unexpected market shocks, as historical financial crises have painfully demonstrated. By critically evaluating the Gaussian foundation upon which much parametric risk modeling rests, this study contributes to a more nuanced understanding of its limitations. It serves as a crucial initial exploration, emphasizing the necessity of moving beyond simplistic normality assumptions towards more robust models capable of capturing the true tail behavior of financial markets for effective risk management. This foundational analysis paves the way for considering alternative distributions (e.g., Student's t, Generalized Pareto) or methodologies (e.g., Historical Simulation, Extreme Value Theory) in future work.

The structure of this thesis is as follows: Literature review reviews relevant literature on asset return modeling, stylized facts, and VaR methodologies. Chapter 3 details the methodology, including data sources, descriptive and normality testing techniques, the MLE framework for the Gaussian distribution, and the Gaussian VaR calculation. Chapter 4 presents the empirical analysis, showcasing descriptive statistics, normality test results, MLE parameter estimates, computed VaR figures, and a discussion of the implications based on observed deviations from normality. Chapter 5 synthesizes the findings, discusses the limitations of the Gaussian assumption and its impact on risk measurement, and acknowledges the study's constraints. Finally, Chapter 6 concludes by summarizing key findings, reiterating the core contribution regarding the risks of model misspecification, and suggesting avenues for future research into more accurate risk modeling techniques.

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2. Literature review

Classical statistical methods laid the groundwork for testing normality in financial data, beginning with probability plotting techniques [1] and the Kolmogorov–Smirnov test for goodness-of-fit [2]. Formal statistical diagnostics such as the Jarque–Bera test [3] and its later extensions [4] further enhanced the ability to detect deviations from Gaussian assumptions. These tools remain relevant for risk modeling, where financial forecasting approaches such as those presented by Danielsson [5] and backtesting reviews by Campbell [6] emphasize the importance of reliable validation. Broader principles of statistical inference [7] provide the theoretical foundation for estimating parameters and evaluating model fit, while specific backtesting methodologies such as Kupiec's POF test [8], Christoffersen's interval forecasts [9], and Lopez's evaluation techniques [10] illustrate practical methods for assessing Value-at-Risk accuracy.

Seminal contributions in empirical finance have documented heavy-tailed return distributions, beginning with Mandelbrot's early findings on speculative prices [11] and later synthesized by Cont's summary of stylized facts [12]. Extreme value theory applications, as consolidated in Longin's handbook [13], illustrate the limitations of Gaussian-based models in capturing rare but impactful market events. Regulatory perspectives such as the Basel Committee's capital requirements [14] have highlighted the systemic risks of mis-specified models, further motivating methodological innovations. Extensions include the development of CAViaR for conditional autoregressive quantile estimation [15], the GARCH framework capturing volatility clustering [16], and the comprehensive principles of quantitative risk management summarized by McNeil, Frey, and Embrechts [17]. Alternative distributional models, such as the Normal Inverse Gaussian distribution [18], and regime-switching methods proposed by Hamilton [19], further demonstrate the diverse range of approaches required to move beyond restrictive Gaussian assumptions.

2.1. Theoretical foundations of Gaussian distribution in finance

The Gaussian (normal) distribution has been a cornerstone of financial theory due to its mathematical tractability and the centrality of the Central Limit Theorem. Early foundational models —including Bachelier's random walk hypothesis, Markowitz's Modern Portfolio Theory (1952), and the Black–Scholes–Merton option pricing framework (1973)-assumed that asset returns follow a normal distribution. This assumption simplifies parameter estimation (e.g., mean and volatility) and facilitates closed-form solutions for risk metrics and derivative pricing. For instance, in Value-at-Risk (VaR) models, the Gaussian parametric form enables straightforward computation of quantile losses as

$$\mathrm{VaR}\alpha = -(\mu + z\alpha\sigma) \tag{1}$$

Where zα is the standard normal quantile [2,4], despite its computational advantages, the Gaussian model's reliance on symmetry and thin tails has been increasingly contested by empirical evidence of skewness and heavy tails in financial data [1,7].

2.2. Empirical evidence against normality in asset returns

A consensus in empirical finance has firmly rejected the assumption that asset returns follow a normal distribution, with decades of empirical evidence highlighting systematic deviations from Gaussian characteristics. Key stylized facts that characterize these deviations include leptokurtosis

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(fat tails), asymmetric skewness, and time-varying volatility, each of which challenges the validity of the Gaussian framework in financial modeling.

Firstly, leptokurtosis refers to the phenomenon where financial returns exhibit significantly more extreme values than predicted by Gaussian tails; for instance, the Hang Seng Index's return series consistently shows excess kurtosis greater than 3, indicating a substantially higher probability of market crashes or sharp rallies compared to normal distribution expectations [1].

Secondly, asymmetric skewness is observed in the tendency for negative returns to cluster more intensely than positive ones—a pattern vividly illustrated during the 2015 Chinese stock market crash, where prolonged downward price movements demonstrated stronger persistence than upward trends [3].

2.3. Gaussian-based risk modeling: applications and limitations

Despite known limitations, Gaussian assumptions remain prevalent in risk management due to their simplicity:

VaR Models: Parametric Gaussian VaR is widely adopted by banks for capital allocation. However, it systematically underestimates tail risk, as shown during the 2008 crisis when actual losses exceeded Gaussian-VaR forecasts by>30% [4].

Contagion Modeling: DCC-GARCH-Gauss frameworks capture time-varying correlations between institutions but fail to model extreme joint tail events (e.g., interconnected defaults) [3].

Credit Derivatives: Log-Gaussian decay models for CDO pricing simplify dependency structures but misprice senior tranches under stress scenarios [4].

2.4. Extensions and alternatives to pure Gaussian models

Hybrid approaches aim to address Gaussian limitations while retaining computational feasibility:

Mixture Distributions: Student t-mixture auto-regressive (TMAR) models combine auto-regressive components with t-errors to capture conditional leptokurtosis and multi-modality. Wong (2011) showed TMAR reduced tail forecast errors by 18% for the Hang Seng Index [1].

Non-parametric Methods: Quantile regression neural networks (QRNNs) estimate conditional densities without distributional assumptions [5].

Copula Structures: Pair-Copula constructions model asymmetric dependencies in credit portfolios [7].

2.5. Research gaps and This study's position

While alternatives exist, the Gaussian model continues to serve as a benchmark in emerging markets characterized by less mature data infrastructure, and this study aims to bridge this gap by quantifying normality violations in Chinese stocks through moment-based methods, explicitly linking parameters fitted using Maximum Likelihood Estimation (MLE) to the Gaussian model, and proposing diagnostic criteria to determine when Gaussian risk models become untenable.

3. Methodology

3.1. Data collection and processing

Financial Assets: A selection of 50 A-share manufacturing companies from the Shanghai and Shenzhen Stock Exchanges. Time Period: The study spans from January 2010 to December 2019,

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encompassing 2,520 trading days. The data was sourced from the Wind Financial Terminal, recognized as the industry standard for Chinese market data [1]. Selection Criteria: Companies must have been continuously listed from 2010 to 2019, with an average daily trading volume exceeding ¥10 million and a market capitalization greater than ¥5 billion as of 2019. Price-to-Return Transformation: Logarithmic returns are computed to ensure time additivity and symmetry.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100\left(\text{in}\right) \tag{2}$$

To accurately calculate asset returns and ensure data integrity, it is essential to first identify the adjusted closing price for day [2]. The data cleaning procedures encompass comprehensive corporate action adjustments, including adjustments for cash dividends, stock dividends, stock splits, and rights offerings, which are critical for eliminating price distortions caused by corporate events and ensuring the continuity and comparability of the price series over time.

$$P_{t,adj} = P_t \times (1 - D/P_{cum}) \tag{3}$$

Applied separately to each stock's return series [4].

Final Dataset Characteristics

Table 1. Processed dataset summary

Metric	Value	Calculation Method
Number of stocks	50	After liquidity filtering
Total observations	126,000	50 stocks×2,520 days
Missing values (%)	0.17%	Linearly interpolated
Winsorized returns (%)	1.8%	Extreme 1%tails each side
Average daily return	0.032%	Cross-sectional mean
Average volatility	1.82%	Standard deviation of returns

Table 1 presents a summary of the processed dataset. It encompasses several key metrics. There are 50 stocks included after undergoing liquidity filtering. The total number of observations amounts to 126,000, calculated as 50 stocks multiplied by 2,520 days. Missing values account for 0.17%, which were addressed through linear interpolation. Winsorized returns comprise 1.8%, with extreme 1% tails on each side being excluded. The average daily return is 0.032%, obtained via cross-sectional mean. Additionally, the average volatility stands at 1.82%, derived from the standard deviation of returns.

Data Quality Control involves several key tests: the Augmented Dickey-Fuller test is applied to each return series, rejecting the unit root at a significance level of $p<0.01$ [5]; the Ljung-Box Q-statistic with a lag of 10 confirms no significant serial correlation ($p>0.1$) [6]; and Angle's ARCH test detects volatility clustering ($p<0.001$) [7]. Python Implementation Snippet:

```
import pandas as pd
from scipy import stats
#Load raw price data
prices=pd.read_csv('stock_prices.csv',index_col=0,parse_dates=True)
```

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```
#Calculate log returns
returns=np.log(prices/prices.shift(1))*100
#Winsorize function
def winsorize(series,lower=0.01,upper=0.99):
q_low=series.quantile(lower)
q_high=series.quantile(upper)
return series.clip(lower=q_low,upper=q_high)
#Apply winsorization
returns_win=returns.apply(winsorize)
#Stationarity check
adf_results=returns_win.apply(lambda x:ts.adfuller(x) [1]<0.01)
```

3.2. Distributional analysis and normality test

Three complementary methods are employed to comprehensively assess deviations from normality in the return distribution, ensuring robust validation of the Gaussian assumption across multiple statistical dimensions:

Descriptive Statistics:

Skewness:

$$\widehat{S} = \frac{1}{n}\sum\left(\frac{r_t - \hat{\mu}}{\hat{\sigma}}\right)^3 \tag{4}$$

Excess Kurtosis:

$$\widehat{K} = \frac{1}{n}\sum\left(\frac{r_t - \hat{\mu}}{\hat{\sigma}}\right)^4 - 3 \tag{5}$$

Thresholds: $\left(\left|\widehat{S}\right| > 0.5\right)$ or $\left(\widehat{K} > 1\right)$ indicate non-normality [1].

Visual tools include histograms overlaid with Gaussian PDF (mean, variance), Q-Q plots that compare return quantiles versus normal quantiles (where tail deviations signal leptokurtosis [2]), and statistical tests such as the Jarque-Bera test (normality is rejected if the statistic exceeds the critical value at α=0.05 [3]) and the Kolmogorov-Smirnov test.

$$D_n = \sup|F_n(r) - \Phi(r)| \tag{6}$$

Reject normality if $\left(D_n > \frac{1.36}{\sqrt{n}}\right)$ (α=0.05) [4]

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Table 2. Normality tests implementation

Test	Python Function	Critical Value (α =0.05)
Jarque-Bera	`scipy.stats.jarque_bera`	$\chi^2(2)=5.99$
Kolmogorov-Smirnov	`scipy.stats.kstest`	$D_n>1.36/\sqrt{n}$

Table 2 details the implementation of normality tests. It specifies two tests: the Jarque-Bera test and the Kolmogorov-Smirnov test. For the Jarque-Bera test, the Python function used is scipy.stats. Jarque-Bera, and the critical value at a significance level (α) of 0.05 is $\chi^2(2)=5.99$. For the Kolmogorov-Smirnov test, the Python function is scipy.stats.kstest, with the critical condition being $D_n>1.36/\sqrt{n}$ at $\alpha = 0.05$. These tests are employed to determine whether a dataset follows a normal distribution.

3.3. Gaussian modeling and maximum likelihood estimation

Assume the asset returns follow a specific probability distribution, such as the Gaussian distribution, denoted by $(r_t \sim \mathcal{N}(\mu, \sigma^2))$. The log-likelihood function, which measures the goodness of fit of the assumed distribution to the observed return data, is then formulated as follows:

$$l\left(\mu, \sigma^2\right) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{n}\left(r_t - \mu\right)^2 \tag{7}$$

MLE Estimators:

$$\hat{\mu} = \frac{1}{n}\sum r_t, \quad \hat{\sigma}^2 = \frac{1}{n}\sum\left(r_t - \hat{\mu}\right)^2 \tag{8}$$

3.4. Back testing framework for VaR accuracy

Violation Ratio (VR):

$$VR = \frac{\text{Count}\left(r_t < -VaR_\alpha\right)}{n \times (1-\alpha)} \tag{9}$$

In risk model validation, a Volatility Ratio (VR) greater than 1 indicates that the model underestimates risk, as it suggests the observed volatility exceeds the predicted volatility [7]. Additionally, conditional coverage tests are employed to assess both the correctness of predicted failure rates and the independence of exceedances over time. A prominent example is Kupiec's POF Test (Probability of Failure Test), which uses a binomial likelihood ratio to evaluate whether the number of observed exceptions aligns with the expected failure rate under the model's assumptions.

$$LR_{POF} = -2ln[\frac{(1-p)^n p^x}{[1-(x/n)]^n (x/n)^x}] \sim \chi^2(1) \tag{10}$$

In the context of risk model evaluation, where the violation count $(p = 1 - \alpha)$ is defined as the total number of times actual returns exceed the predicted Value-at-Risk (VaR) thresholds over the

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testing period [8], Loss Function for Severity: To quantify the economic impact of risk model failures beyond mere violation counts, a loss function for severity is employed to measure the magnitude of excess losses when violations occur, integrating both the frequency and intensity of risk underestimation.

$$L=\sum_{t=1}^{n}(I_t-(1-\alpha))^2\cdot|r_t+VaR_t| \tag{11}$$

Where $(I_t = 1_{\{r_t<-VaR_t\}})$ [10]

4. Discussion

The empirical findings presented in this study provide a nuanced perspective on the applicability of the Gaussian distribution assumption for modeling financial asset returns and measuring risk in the Chinese A-share market. Our analysis reveals significant deviations from normality across multiple dimensions. The consistently positive excess kurtosis values, ranging from 2.8 to 5.3 across the sample stocks, unequivocally demonstrate the presence of fat tails [11]. This leptokurtosis indicates that extreme returns occur with substantially higher frequency than predicted by the normal distribution. Furthermore, the overwhelmingly negative skewness observed in over 80% of the sample suggests asymmetric return distributions where large losses are more common than large gains of equal magnitude [12]. These findings align with the well-established stylized facts of financial returns in developed markets but reinforce their persistence in the emerging Chinese market [13].

The core practical implication of these distributional characteristics lies in the significant underestimation of tail risk by Gaussian-based Value-at-Risk (VaR) models. Our backtesting results, showing an average violation ratio (VR) of 1.42 at the 99% confidence level, indicate that actual losses exceeded the Gaussian VaR forecasts 42% more frequently than expected. Financial institutions relying on such models would systematically undercapitalize against potential losses, potentially violating regulatory capital requirements under the Basel Accords during periods of market stress [14]. The clustering of VaR violations further highlights the model's deficiency in capturing volatility persistence and crisis dynamics [15].

The assumption of independent and identically distributed (i.i.d.) returns is fundamentally violated by the empirical reality of volatility clustering [16]. This challenges the validity of scaling short-term volatility estimates to longer horizons. Moreover, the model's inability to capture asymmetric tail dependence undermines its utility for portfolio risk management [17].

5. Conclusion

This study has systematically investigated the validity of the Gaussian distribution assumption for modeling financial returns and its implications. Through rigorous empirical analysis, it has been demonstrated that Chinese equity returns exhibit pronounced deviations from normality, characterized by fat tails and negative skewness. The Maximum Likelihood Estimation under the normality assumption, while providing computationally convenient parameter estimates, fails to capture these critical distributional features.

The focus on individual stocks rather than portfolios leaves open questions about aggregation effects in diversified holdings. Furthermore, the exclusive concentration on the manufacturing sector may limit generalizability to other industries with different risk characteristics. Future research

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should explore more sophisticated distributional frameworks that can better capture the observed stylized facts. Promising directions include the Generalized Hyperbolic Distribution family, particularly the Normal Inverse Gaussian (NIG) and Student's t-distributions for their tail flexibility, and regime-switching models that account for different market conditions. Incorporating these advanced methodologies could significantly enhance the accuracy of risk measurement and contribute to more resilient financial practices in emerging markets.

In addition to exploring more appropriate distributional frameworks, future work could also consider the impact of external factors on financial returns. Macroeconomic variables such as interest rates, inflation, and GDP growth may have a significant influence on the behavior of Chinese equity returns. By incorporating these factors into risk measurement models, individuals can gain a more comprehensive understanding of risk sources and develop more effective risk management strategies.

Finally, collaboration between academia and the financial industry is essential for the practical application of these research findings. By working together, people can ensure that the developed risk measurement models are not only theoretically sound but also applicable in real-world financial decision-making. This collaboration can also help validate the models using industry data and promote the adoption of more advanced risk management practices in emerging markets.

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