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The Characteristics of Fruit Price Fluctuations and Their Risk Management in China: A Case Study of Apples, Bananas, and Grapes

Jingbing Gao

Xiamen University Malaysia

Email: DSC2209252@xmu.edu.my

Abstract:

This study analyzes price fluctuations of apples, bananas, and grapes using quantitative and qualitative methods. Based on price data from January 31, 2014, to January 19, 2024, GARCH models are applied to study price volatility, and the Value at Risk (VaR) method is used for risk management. The results show significant fruit price volatility, with log-returns having a leptokurtic distribution. Prices of apples and grapes display conditional heteroskedasticity, fitting well with GARCH models, while bananas do not, making GARCH unsuitable for them. Among three distribution assumptions (normal, Student's t, and GED), the GED model provides the best fit. Further findings reveal a mismatch between returns and risk for apples, while grapes exhibit a high-risk, high-return profile. Additionally, apple prices lack asymmetry, whereas grape prices do show asymmetric volatility. VaR back-testing confirms the model's reliability, especially at a 99% confidence level with zero failure rate. This research provides practical tools for fruit market risk management, aiding in resource allocation, hedging strategies, and risk cost reduction.

Keywords: fruits, price fluctuation, ARCH family models, risk management

1. Introduction

1.1 Research Background and Significance, Research Content and Innovations

With the intensification of global marketization and climate change, fruit prices are experiencing frequent and drastic fluctuations. Price volatility not only affects the income of agricultural producers but also has a direct impact on the decisions of wholesalers, retailers, and consumers. However, current research on fruit price volatility is relatively limited, especially in the systematic analysis of risk management, which has not received sufficient attention. Fruit price fluctuations are influenced by various factors, such as climate, changes in supply and demand, and market policies, making research difficult; existing studies often focus on superficial patterns or single characteristics.

This study will integrate the Value at Risk (VaR) method and Autoregressive Conditional Heteroskedasticity (ARCH) models to analyze the volatility and potential risks of fruit prices in depth. These models are widely used in the financial field and can handle complex market volatility characteristics, providing a basis for formulating reasonable risk management strategies. By applying actual market data, this study aims to provide effective risk mitigation and market decision-making references for agricultural producers, wholesalers, and policymakers, filling the existing gap in comprehensiveness and systematicity in current research.

1.2 Literature Review

In China, Lv Jianxing and others analyzed the price fluctuations of apples, oranges, and bananas using X12 and HP filtering methods, revealing seasonal and trend characteristics of fruit prices [1]. Wang Junqin pointed out that apple prices do not exhibit the “high risk, high return” characteristic [2]. Guo Qiusheng used VAR models to analyze the horizontal spillover effects of fruit prices, finding that price increases among different fruits are transmissible [3]. Additionally, Hu Weitong applied a multivariate GARCH model and found that apple price volatility exhibits asymmetrical characteristics [4], while Qi Wenge and others suggested that perishability is the main reason for the asymmetric characteristics of lychee price fluctuations [5]. Internationally, Gandorfer concluded through Levene’s test that producers can reduce price risks by optimizing sales channels [6]. Felis and Garrido employed multivariate GARCH models to analyze the price fluctuation patterns of fresh fruits and vegetables in Spain [7]. Sidhoum and Serra studied the market transmission of price fluctuations in the tomato marketing chain, providing powerful tools for managing price risk [8]. Meanwhile, Yang and others applied GARCH to analyze the impact of agricultural sector liberalization on commodity price volatility, revealing that agricultural liberalization policies exacerbate market fluctuations for certain grain crops, emphasizing the potential impact of these policies on the market, particularly in the commodity sector [9]. Anggraeni and others used vector autoregression models and ARIMAX models to forecast rice price fluctuations in Indonesia, providing important insights into rice market price trends [10]. However, current research is still largely focused on single dimensions of price volatility, with limited studies on how to systematically manage fruit price risks.

In summary, existing research primarily focuses on fruit price fluctuations and risk management. Researchers have employed various methods, including GARCH models, ARCH models, MGARCH models, VAR models, and ARIMAX models, to analyze price volatility characteristics, asymmetrical features of price fluctuations, and price fluctuation patterns under the interactions of multiple agricultural products. Current studies tend to be limited to superficial patterns of fruit price fluctuations or specific characteristics of price volatility, with little comprehensive analysis of how to manage price risks. Therefore, future research could focus on systematically analyzing the fundamental causes of price fluctuations in different agricultural product markets to better mitigate risks and guide market and production decisions.

2 Research Methods and Theoretical Framework

This study employs a comprehensive approach utilizing both qualitative and quantitative methods to analyze the price volatility of apples, bananas, and grapes and to investigate associated risks.

The qualitative research method primarily focuses on the factors influencing fruit prices as well as the inherent properties and characteristics of the fruits. It begins by making preliminary assessments of market risks and then conducts a comprehensive risk measurement, offering corresponding regulatory recommendations.

The quantitative research method primarily involves using Eviews software to analyze the descriptive characteristics of the price series of apples, bananas, and grapes from January 31, 2014, to January 19, 2024. This analysis includes testing for correlations and ARCH effects, establishing GARCH family models under different distribution assumptions, and conducting a comparative evaluation based on AIC, SC, chi-square distribution, and maximum likelihood estimation to select the optimal model for fitting. The model is then developed in Eviews, where the Value at Risk (VaR) of fruit prices is calculated, followed by visualization and forecasting. A sample is selected for back-testing to compare the number of failures and failure probabilities. Additionally, the LR statistic is calculated using Python to derive conclusions from the quantitative research.

2.1 GARCH Model, GARCH-M Model and TGARCH Model

2.1.1 GARCH Model

The GARCH model, proposed in 1986, is a type of regression model based on the phenomenon of volatility clustering in time series data and is an extension of the ARCH model; hence, it is called the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. By expanding the treatment of error terms in the equations, the GARCH model reduces unnecessary interference. Its core idea is to relate current volatility with historical volatility, making the variance at each time period a conditional variance. By expressing the current conditional variance as a linear combination of multiple past conditional variances, it further enhances the model's capability to describe and predict volatility.

Expression:

Mean equation: $\alpha_t = \sigma_t \epsilon_t$

Variance equation: $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \alpha_{t-i}^2 + \sum_{q}^{j=1} \beta_j \sigma_{t-j}^2$

Explanation:

The mean equation includes a residual term, which is a sequence of random variables with a mean of zero and a variance of one. The variance equation contains conditional variance. The equation must satisfy the following conditions: α_0 >0, α_i >=0, β_j >=0 and 0< $\sum_{i-1}^{max(p,q)} (\alpha_i + \beta_j)$ <1.

Limitations of the GARCH model: The GARCH model assumes symmetric responses to positive and negative shocks, making it unable to capture the leverage effect often seen in financial markets, where negative shocks typically have a larger impact than positive ones. To address this limitation, improved models such as EGARCH and TGARCH were later proposed to better handle asymmetry.

2.1.2 GARCH-M Model

The GARCH-M model is another extension of the GARCH model, making a breakthrough by introducing the disturbance term β into the equation to describe the autoregressive process, thereby reducing the impact of disturbances on the model. Volatility can affect time series variables, especially in cases where the price of an asset or asset portfolio is influenced not only by external factors but also by its volatility. By incorporating volatility into the model, the GARCH-M model allows for a more accurate measurement of changes in asset prices.

Expression:

Mean equation: $r_t = \mu + c\sigma_t^2 + a_t$

Variance equation: $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \alpha_{t-i}^2 + \sum_{q}^{j=1} \beta_j \sigma_{t-j}^2$

Explanation:

Compared to the GARCH model, the residuals in the mean equation of the GARCH-M model are transformed into standard deviations.

2.1.3 TGARCH Model

The TGARCH model, also known as the Threshold ARCH model, innovatively introduces an additional term, ω, to account for asymmetry in volatility. This model can distinguish the differing impacts of positive and negative shocks on volatility, meaning that negative shocks (such as bad news) often cause greater volatility, while positive shocks (such as good news) have a smaller effect. The introduction of this asymmetry enables the TGARCH model to more accurately characterize time series with asymmetric volatility features, such as those in financial markets.

Expression:

Mean equation: $\alpha_t = \sigma_t \epsilon_t$

Variance equation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \alpha_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \alpha_{t-i}^2 d_{t-i} + \sum_{q}^{j=1} \beta_j \sigma_{t-j}^2$$

Explanation:

The TGARCH model introduces significant changes compared to the GARCH model, where $\gamma\mu_{t-1}^2 d_{t-1}$ represents the asymmetric effect term, also known as the TGARCH term, and d_{t-1} is a dummy variable. If μ_t >0, it indicates good news, or a positive shock; whereas if μ_t <0, it indicates bad news, or a negative shock. If γ=0, it means that the conditional heteroskedasticity does not exhibit a leverage effect in response to shocks.

2.2 Value at risk (Var)

Expression:

Prob ($?P_{?t} > Var$) = c

Explanation:

Here, $?P_{?t}$ represents the maximum loss of a fruit or fruit portfolio over the holding period $?t$, and VaR is the risk value at the confidence level c, indicating the upper limit of potential losses that may occur. Therefore, it is essential to know the confidence level, the holding period in days, and the probability distribution of future returns for the fruit or fruit portfolio.

3. Empirical Analysis

3.1 Statistical Analysis of Data

Descriptive Analysis of Fruit Price Trends:

Based on the annual price fluctuations of apples, bananas, and grapes, this study selects weekly data from January 21, 2014, to January 19, 2024, for these three fruits, with each fruit comprising 521 samples. The data is sourced from the website of the Department of Market Operation and Consumption Promotion of the Ministry of Commerce.

Figure 1 Price Trend of Apples from January 21, 2014, to January 19, 2024.

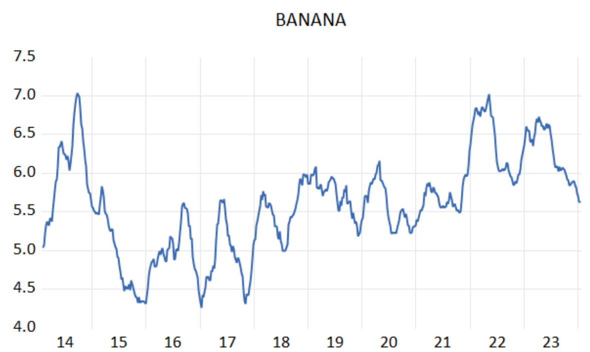


Figure 2 Price Trend of Bananas from January 21, 2014, to January 19, 2024.

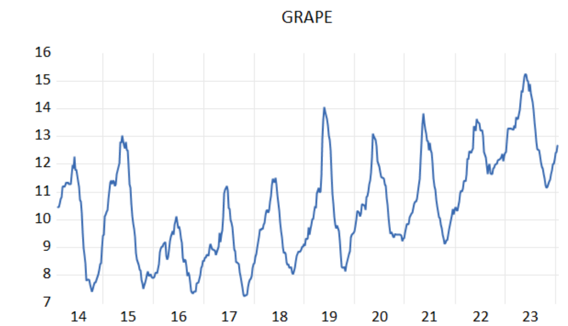


Figure 3 Price Trend of Grapes from January 21, 2014, to January 19, 2024.

It was observed that the price trends of the three fruits are volatile. Therefore, their logarithmic returns are calculated.

The formula for logarithmic return is:

$$r_t = lnP_t - lnP_t (t = 1, 2, 3...)$$

According to the formula, the price fluctuations of apples, bananas, and grapes are expressed as the first-order difference of their logarithmic prices, representing the logarithmic returns of the fruits. Here, r_t denotes the logarithmic return on day t, and P_t represents the price of a fruit on day t. In this study, the logarithmic returns of apples, bananas, and grapes are used as data to empirically measure the market risk of fruits.

Subsequently, a descriptive analysis of the fruits' price return data is conducted.

Table 1 Descriptive Statistics Table of Logarithmic Returns for Fruit Prices.

	Dlog(APPLE)	Dlog(BANANA)	Dlog(GRAPE)
Mean	0.000355	0.000209	0,000370
Median	0.001200	0.000000	0.001094
Maximum	0.071105	0.051804	0.106822
Minimum	-0.078097	-0.047628	-0.071547
Std. Dev.	0.015560	0.015270	0.024188
Skewness	-0.537868	0.110705	0.022011
Kurtosis	6.636778	3.479335	3.999531
Jarque-Bera	311.6395	6.040329	21.68835
Probability	0.000000	0.048793	0.000020
Sum	0.184764	0.108721	0.192635
Sum Sq. Dev.	0.125657	0.121022	0.303655
ADF Test	0.0045	0.0000	0.0000
Observations	520	520	520

From Table 1, it can be observed that the skewness of the logarithmic returns for apple prices is negative, while those for banana and grape prices are positive. This indicates that the fluctuations in apple price logarithmic returns exhibit a left-skewed distribution compared to the normal distribution, whereas those for bananas and grapes exhibit a right-skewed distribution.

The kurtosis values for the logarithmic returns of all three fruits exceed 3, suggesting that the logarithmic returns of apple, banana, and grape prices exhibit characteristics of leptokurtosis and fat tails.

According to the JB normality test results, the null hypothesis that the fluctuations in logarithmic returns follow a normal distribution is rejected at the 1% significance level for all three fruits. This indicates that the logarithmic returns significantly deviate from a normal distribution.

Based on the results of the ADF stationarity test, the p-values for apples, bananas, and grapes are 0.0045, 0.0000, and 0.0000, respectively. Since all p-values are statistically significant, it can be concluded that the logarithmic returns of the prices of all three fruits exhibit stationarity.

3.2 Mean Model Selection

Through experimentation, it was found that ARMA(1,1) is the optimal model for apples and bananas.

3.2.1 Apple ARMA Model Order Selection (Model Building, Residual Test, Residual ARCH Effect Test)

Through experimentation, it was found that the ARMA(1,1) model is the optimal model for apples. Therefore, the residuals of the fitted model are tested as follows:

Correlogram of Residuals

Date: 08/27/24 Time: 15:01
Sample (adjusted): 2/07/2014 1/19/2024
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	0.006	0.006	0.0188	
2	-0.049	-0.049	1.2888	
3	-0.009	-0.008	1.3288	0.249
4	0.093	0.091	5.8610	0.053
5	0.089	0.088	10.026	0.018
6	-0.010	-0.002	10.077	0.039
7	-0.008	0.002	10.110	0.072
8	0.005	-0.002	10.124	0.120
9	0.006	-0.011	10.142	0.181
10	0.015	0.008	10.255	0.248
11	-0.105	-0.105	16.102	0.065
12	-0.084	-0.085	19.844	0.031
13	-0.054	-0.066	21.419	0.029
14	-0.004	-0.016	21.428	0.044
15	0.014	0.025	21.530	0.063
16	-0.110	-0.080	27.995	0.014
17	-0.025	-0.000	28.331	0.020
18	0.023	0.028	28.611	0.027
19	-0.083	-0.089	32.383	0.013
20	0.003	0.019	32.388	0.020
21	-0.131	-0.125	41.771	0.002
22	-0.039	-0.058	42.599	0.002
23	-0.033	-0.055	43.207	0.003
24	0.104	0.094	49.092	0.001
25	-0.086	-0.090	53.174	0.000
26	-0.017	0.023	53.340	0.001
27	0.089	0.086	57.698	0.000
28	-0.052	-0.086	59.162	0.000
29	-0.002	0.002	59.165	0.000
30	-0.019	-0.032	59.356	0.000
31	0.093	0.076	64.106	0.000
32	0.058	0.009	65.969	0.000
33	-0.054	-0.071	67.620	0.000
34	0.065	0.058	69.955	0.000
35	0.065	0.040	72.304	0.000
36	0.002	-0.012	72.305	0.000

Figure 4 Residual Test Results for Apples.

Correlogram of Residuals Squared

Date: 08/27/24 Time: 15:02
Sample (adjusted): 2/07/2014 1/19/2024
Included observations: 520 after adjustments

	AC	PAC	Q-Stat	Prob
1	0.140	0.140	10.231	0.001
2	0.043	0.024	11.186	0.004
3	0.010	0.000	11.235	0.011
4	0.071	0.070	13.853	0.008
5	0.144	0.128	24.755	0.000
6	0.089	0.051	28.900	0.000
7	0.046	0.022	30.043	0.000
8	-0.014	-0.031	30.147	0.000
9	-0.016	-0.030	30.291	0.000
10	0.023	0.005	30.571	0.001
11	0.156	0.139	43.557	0.000
12	0.070	0.026	46.175	0.000
13	0.064	0.052	48.348	0.000
14	0.007	-0.002	48.373	0.000
15	-0.002	-0.021	48.376	0.000
16	0.125	0.093	56.798	0.000
17	0.076	0.019	59.931	0.000
18	0.075	0.035	62.974	0.000
19	0.032	0.020	63.538	0.000
20	0.052	0.046	65.009	0.000
21	0.147	0.122	76.825	0.000
22	0.063	-0.010	79.013	0.000
23	-0.014	-0.066	79.120	0.000
24	0.047	0.029	80.309	0.000
25	0.059	0.033	82.220	0.000
26	0.011	-0.031	82.288	0.000
27	0.074	0.042	85.310	0.000
28	0.024	-0.001	85.634	0.000
29	-0.052	-0.092	87.143	0.000
30	-0.048	-0.050	88.438	0.000
31	0.078	0.081	91.776	0.000
32	0.078	0.003	95.188	0.000
33	0.024	-0.013	95.508	0.000
34	-0.042	-0.042	96.516	0.000
35	-0.017	-0.008	96.676	0.000
36	-0.011	-0.032	96.738	0.000

Figure 5 Squared Residual Test Results for Apples.

According to the autocorrelation test results of the ARMA model residuals in Figure 4 and 5, it can be seen that the sample autocorrelation functions at lag 1 all fall within the confidence interval, and the Q-statistic is not zero. This indicates that the ARMA(1,1) model has eliminated the autocorrelation of the residuals.

Then, an ARCH-LM test is conducted to assess the loga-

Heteroskedasticity Test: ARCH

F-statistic	10.32165	Prob. F(1,517)	0.0014
Obs*R-squared	10.15877	Prob. Chi-Square(1)	0.0014

Lag 2:

Heteroskedasticity Test: ARCH

F-statistic	5.269923	Prob. F(2,515)	0.0054
Obs*R-squared	10.38863	Prob. Chi-Square(2)	0.0055

Figure 6 ARCH-LM Test Results for Apples.

The ARCH-LM test is conducted on the apple sample series for both lag 1 and lag 2. According to the results in Figure 6, the F-statistic and the goodness-of-fit probabilities are both close to 0 and are significant. Therefore, it can be concluded that the sample series exhibits ARCH effects.

3.2.2 Grapes

Through experimentation, it was found that the ARMA(1,1) model is the optimal model for grapes. Therefore, the residuals of the fitted model are tested as follows:

Correlogram of Residuals

Date: 09/03/24 Time: 17:58
Sample (adjusted): 2/07/2014 1/19/2024
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0023	
		2	0.002	0.002	0.0043	
		3	-0.020	-0.020	0.2067	0.649
		4	0.053	0.053	1.6889	0.430
		5	0.031	0.031	2.1930	0.533
		6	-0.012	-0.013	2.2697	0.686
		7	0.025	0.027	2.5946	0.762
		8	-0.034	-0.036	3.2221	0.780
		9	0.081	0.078	6.7386	0.457
		10	-0.035	-0.034	7.3901	0.495
		11	-0.073	-0.077	10.236	0.332
		12	-0.028	-0.023	10.670	0.384
		13	0.002	-0.005	10.672	0.471
		14	-0.007	-0.012	10.695	0.555
		15	0.006	0.018	10.712	0.635
		16	0.005	0.006	10.726	0.707
		17	-0.090	-0.085	15.128	0.442
		18	-0.056	-0.061	16.841	0.396
		19	-0.096	-0.097	21.789	0.193

Figure 7 Residual Test Results for Grapes.

Correlogram of Residuals Squared

Date: 09/03/24 Time: 17:59
Sample (adjusted): 2/07/2014 1/19/2024
Included observations: 520 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.126	0.126	8.3422	0.004
		2	-0.024	-0.040	8.6358	0.013
		3	0.110	0.120	15.009	0.002
		4	0.070	0.039	17.567	0.001
		5	0.104	0.102	23.319	0.000
		6	-0.009	-0.045	23.359	0.001
		7	0.034	0.040	23.963	0.001
		8	0.057	0.021	25.715	0.001
		9	0.064	0.056	27.874	0.001
		10	0.066	0.041	30.198	0.001
		11	0.052	0.041	31.620	0.001
		12	0.025	-0.004	31.957	0.001
		13	0.024	0.005	32.277	0.002
		14	-0.028	-0.057	32.700	0.003
		15	0.014	0.012	32.800	0.005
		16	0.065	0.046	35.081	0.004
		17	-0.011	-0.022	35.147	0.006
		18	-0.080	-0.084	38.567	0.003
		19	0.029	0.036	39.008	0.004
		20	0.020	-0.012	39.234	0.006
		21	-0.042	-0.037	40.203	0.007
		22	-0.070	-0.060	42.902	0.005
		23	-0.001	0.023	42.903	0.007

Figure 8 Squared Residual Test Results for Grapes.

According to the autocorrelation test results of the ARMA model residuals in Figure 7 and 8, it can be seen that the sample autocorrelation functions at lag 1 all fall within the confidence interval, and the Q-statistic is not zero. This indicates that the ARMA(1,1) model has eliminated the autocorrelation of the residuals.

According to the autocorrelation test results of the ARMA model residuals in Figure 7 and 8, it can be observed that the sample autocorrelation functions at lag 1 all fall within the confidence interval, and the Q-statistic is not zero. This indicates that the ARMA(1,1) model has successfully removed the autocorrelation in the residuals.

Then, an ARCH-LM test is conducted to assess the logarithmic returns of grapes:

Lag 1:

Heteroskedasticity Test: ARCH

F-statistic	8.387482	Prob. F(1,517)	0.0039
Obs*R-squared	8.285510	Prob. Chi-Square(1)	0.0040

Lag 2:

Heteroskedasticity Test: ARCH

F-statistic	4.571874	Prob. F(2,515)	0.0108
Obs*R-squared	9.036570	Prob. Chi-Square(2)	0.0109

Figure 9 ARCH-LM Test Results for Grapes.

The ARCH-LM test is conducted on the sample series for both lag 1 and lag 2. According to the results in Figure 9, the F-statistic and the goodness-of-fit probabilities are both close to 0 and are significant. Therefore, it can be concluded that the sample series exhibits ARCH effects.

3.2.3 Banana

Based on the autocorrelation, partial autocorrelation, and Q-test results, it can be concluded that the price of bananas does not exhibit ARCH effects, meaning it does not have conditional heteroscedasticity.

3.3 GARCH Model Estimation and Result Analysis

3.3.1 GARCH

The GARCH(1,1) model is established to fit the logarithmic returns of apples and grapes. It was found that both the residuals and the squared residuals after fitting the model are not significant, indicating that the model fits the data well.

Table 2 GARCH(1,1) Model Estimation Results for Apples.

Parameters/Distribution	Normal	Student's t	GED
ω (Prob.)	6.79E-06 (0.0369)	6.59E-06 (0.1395)	6.42E-06 (0.1777)
α (Prob.)	0.068923 (0.0006)	0.079370 (0.0131)	0.077576 (0.0198)
β (Prob.)	0.897817 (0.0000)	0.893278 (0.0000)	0.892550 (0.0000)

AIC	-5.754966	-5.801958	-5.814654
SC	-5.705811	-5.744611	-5.757307
Adjusted R^2	0.184115	0.181994	0.178663
Log likelihood	1499.414	1512.608	1515.903

Table 3 GARCH(1,1) Model Estimation Results for Grapes.

Parameters/Distribution	Normal	Student's t	GED
ω (Prob.)	0.000380 (0.4262)	0.000585 (0.4944)	3.10E-05 (0.1184)
α (Prob.)	0.150000 (0.3671)	0.150000 (0.5249)	0.097263 (0.0085)
β (Prob.)	0.600000 (0.2005)	0.600000 (0.2753)	0.830665 (0.0000)
AIC	-4.592137	-4.326195	-5.001212
SC	-4.542982	-4.268848	-4.943864
Adjusted R^2	0.298047	0.215891	0.297472
Log likelihood	1197.660	1129.648	1304.814

Based on the results from Table 2 and 3, it can be concluded that apples and grapes have the best fit under the GED distribution, as indicated by the smallest AIC and SC indices. Additionally, both the ARCH and GARCH coefficients are significant, suggesting the presence of volatility clustering. This means that current prices have a lasting impact on future prices. The prices of apples and grapes are significantly affected by supply and demand; when prices are high, supply is insufficient, and when prices are low, supply exceeds demand, leading to persistent price fluctuations and lasting effects on future price movements.

3.3.2 GARCH-M

The GARCH-M(1,1) model is established to fit the logarithmic returns of apples and grapes.

Table 4 GARCH-M(1,1) Model Estimation Results for Apples.

Parameters/Distribution	Normal	Student's t	GED
σ_t (Prob.)	-4.469384 (0.7167)	-2.112159 (0.8287)	3.345346 (0.7054)
ω (Prob.)	6.67E-06 (0.0410)	6.65E-06 (0.1387)	6.13E-0.6 (0.1833)
α (Prob.)	0.068879 (0.0006)	0.078520 (0.0129)	0.078510 (0.0191)
β (Prob.)	0.898503 (0.0000)	0.893416 (0.0000)	0.893772 (0.0000)
AIC	-5.751479	-5.798209	-5.810993
SC	-5.694131	-5.732669	-5.745454
Adjusted R^2	0.183472	0.181316	0.174459
Log likelihood	1499.509	1512.635	1515.953

Table 5 GARCH-M(1,1) Model Estimation Results for Grapes.

Parameters/Distribution	Normal	Student's t	GED
σ_t (Prob.)	-16.53839 (0.0327)	-17.01310 (0.0267)	-15.13018 (0.0392)
ω (Prob.)	2.38E-05 (0.0527)	2.14E-05 (0.1077)	2.18E-05 (0.1253)
α (Prob.)	0.114347 (0.0000)	0.122705 (0.0005)	0.123151 (0.0006)
β (Prob.)	0.836865 (0.0000)	0.839749 (0.0000)	0.836153 (0.0000)
AIC	-4.988239	-5.001515	-5.004430
SC	-4.930892	-4.935975	-4.938890
Adjusted R^2	0.302398	0.303816	0.303856
Log likelihood	1301.448	1305.893	1306.650

The GARCH-M(1,1) models for apples and grapes are shown in Table 4 and 5. By comparing the AIC, SC index, and log-likelihood values from these tables, it can be concluded that the GARCH-M model under the GED distribution provides the best fit for both apples and grapes.

For apples, the risk-return coefficient is not significant, indicating that it does not exhibit the high-risk, high-return characteristic. In contrast, grapes show the opposite trend, exhibiting high-risk, high-return characteristics. Apples experience high production risks due to natural risks, market fluctuations, and other factors, but farmers cannot influence prices through controlling supply. As a result, the returns do not align with the risks. Grapes, on the other hand, are more susceptible to climate conditions, pests, and diseases, but they can yield high returns under favorable conditions. Additionally, technical support and policies also influence grape production, giving them an overall high-risk, high-return profile.

3.3.3 TGARCH

The TGARCH(1,1) model is established to fit the logarithmic returns of apples and grapes.

Table 6 TGARCH(1,1) Model Estimation Results for Apples.

Parameters/Distribution	Normal	Student's t	GED
ω (Prob.)	5.32E-0.6 (0.0523)	6.01E-0.6 (0.1533)	5.48E-0.6 (0.2008)
α (Prob.)	0.081800 (0.0016)	0.085747 (0.0301)	0.088873 (0.0367)
β (Prob.)	0.911374 (0.0000)	0.897901 (0.0000)	0.901614 (0.0000)
γ (Prob.)	-0.035623 (0.2186)	-0.015817 (0.7279)	-0.028419 (0.5451)
AIC	-5.753223	-5.798340	-5.811592
SC	-5.695876	-5.732800	-5.746052
Adjusted R^2	0.183237	0.181821	0.178059
Log likelihood	1499.961	1512.669	1516.108

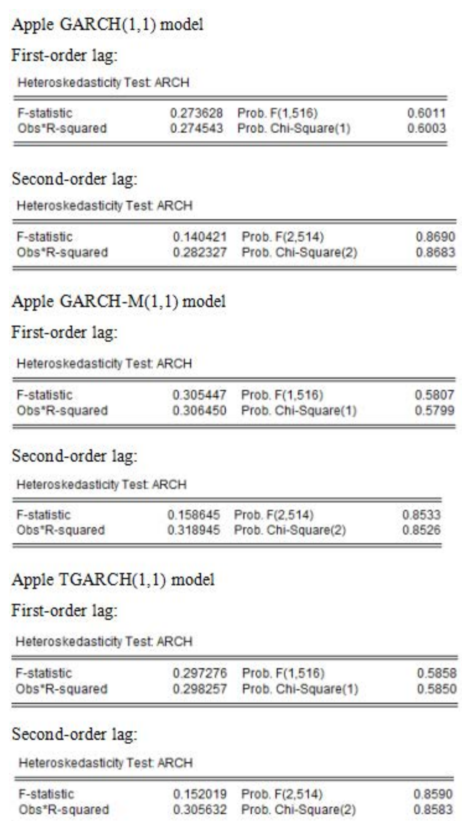
Table 7 TGARCH(1,1) Model Estimation Results for Grapes.

Parameters/Distribution	Normal	Student's t	GED
ω (Prob.)	1.58E-05 (0.0988)	0.000585 (0.4236)	1.53E-05 (0.1970)
α (Prob.)	0.144187 (0.0001)	0.150000 (0.4623)	0.140590 (0.0030)
β (Prob.)	0.880764 (0.0000)	0.600000 (0.1966)	0.881128 (0.0000)
γ (Prob.)	-0.112893 (0.0037)	0.050000 (0.8543)	-0.105831 (0.0332)
AIC	-4.994514	-4.222795	-5.005984
SC	-4.937167	-4.157255	-4.940444
Adjusted R^2	0.295717	0.006059	0.296677
Log likelihood	1303.076	1103.815	1307.053

Based on the results from Table 6 and 7, comparing the AIC, SC index, and log-likelihood values shows that the GARCH-M model under the GED distribution provides the best fit for both apples and grapes.

For apples, the asymmetric effect is significant, but the coefficient is small, indicating that there is no significant asymmetric effect. On the other hand, grapes exhibit a more pronounced asymmetric effect. Due to the perennial nature of apple cultivation, farmers respond weakly to price fluctuations and are unable to quickly adjust production levels. Grapes, however, are significantly influenced by natural factors such as climate and soil, leading to asymmetry in production. This results in larger fluctuations in both yield and prices.

3.3.4 GARCH Family Model ARCH-LM Test Results



Apple GARCH(1,1) model

First-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.273628	Prob. F(1,516)	0.6011
Obs*R-squared	0.274543	Prob. Chi-Square(1)	0.6003

Second-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.140421	Prob. F(2,514)	0.8690
Obs*R-squared	0.282327	Prob. Chi-Square(2)	0.8683

Apple GARCH-M(1,1) model

First-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.305447	Prob. F(1,516)	0.5807
Obs*R-squared	0.306450	Prob. Chi-Square(1)	0.5799

Second-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.158645	Prob. F(2,514)	0.8533
Obs*R-squared	0.318945	Prob. Chi-Square(2)	0.8526

Apple TGARCH(1,1) model

First-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.297276	Prob. F(1,516)	0.5858
Obs*R-squared	0.298257	Prob. Chi-Square(1)	0.5850

Second-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.152019	Prob. F(2,514)	0.8590
Obs*R-squared	0.305632	Prob. Chi-Square(2)	0.8583

Figure 10 ARCH-LM Test Results for GARCH(1,1), GARCH-M(1,1), and TGARCH(1,1) Models for Apples.

Grape GARCH(1,1) model

First-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.347405	Prob. F(1,516)	0.5558
Obs*R-squared	0.348517	Prob. Chi-Square(1)	0.5550

Second-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.959120	Prob. F(2,514)	0.3839
Obs*R-squared	1.922263	Prob. Chi-Square(2)	0.3825

Grape GARCH-M(1,1) model

First-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.169136	Prob. F(1,516)	0.6811
Obs*R-squared	0.169736	Prob. Chi-Square(1)	0.6803

Second-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.984080	Prob. F(2,514)	0.3745
Obs*R-squared	1.972096	Prob. Chi-Square(2)	0.3730

Grape GARCH-M(1,1) model

First-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.164286	Prob. F(1,516)	0.6854
Obs*R-squared	0.164870	Prob. Chi-Square(1)	0.6847

Second-order lag:

Heteroskedasticity Test: ARCH

F-statistic	0.594037	Prob. F(2,514)	0.5525
Obs*R-squared	1.192253	Prob. Chi-Square(2)	0.5509

Figure 11 ARCH-LM Test Results for GARCH(1,1), GARCH-M(1,1), and TGARCH(1,1) Models for Grapes.

Based on the results in Figure 10 and 11, it can be observed that the F-statistic and corresponding p-values are significant. Therefore, we accept the null hypothesis, indicating that the residuals do not exhibit conditional heteroscedasticity. This suggests that the three models under the GED distribution (GARCH(1,1), GARCH-M(1,1), and TGARCH(1,1)) have successfully eliminated the ARCH effect, allowing for risk measurement based on these models.

4. Risk Management

4.1 VaR Calculation and Backtesting

4.1.1 Apple

Using EViews to establish GARCH, GARCH-M, and TGARCH models, and to calculate and backtest the Value at Risk (VaR) for apples.

Table 8 VaR Values for Apples Using the GARCH Model at Different Confidence Levels.

Confidence Level	VaR Minimum Value	VaR Maximum Value	VaR Average Value
90%	-0.0188815	-0.0069165	-0.0126034
95%	-0.0248652	-0.0130846	-0.0182652
99%	-0.0386206	-0.0248544	-0.0300064

Table 9 Failure Test Probability Results for VaR Values of Apples Using the GARCH Model.

Confidence Level (c)	Failure Count (N)	Standard Count (T)	Failure Rate (N/T)	Standard Failure Rate (P*)	LR Value
90%	7	105	6.67%	10%	1.451546
95%	2	105	1.9%	5%	2.744434
99%	0	105	0%	1%	2.110570

Table 10 VaR Values for Apples Using the GARCH-M Model at Different Confidence Levels.

Confidence Level	VaR Minimum Value	VaR Maximum Value	VaR Average Value
90%	-0.0188815	-0.0069165	-0.0126034
95%	-0.0248652	-0.0130846	-0.0182652
99%	-0.0386206	-0.0248544	-0.0300064

Table 11 Failure Test Probability Results for VaR Values of Apples Using the GARCH-M Model.

Confidence Level (c)	Failure Count (N)	Standard Count (T)	Failure Rate (N/T)	Standard Failure Rate (P*)	LR Value
90%	7	105	6.67%	10%	1.451546
95%	2	105	1.9%	5%	2.744434
99%	0	105	0%	1%	2.110570

Table 12 VaR Values for Apples Using the TGARCH Model at Different Confidence Levels.

Confidence Level	VaR Minimum Value	VaR Maximum Value	VaR Average Value
90%	-0.0182529	-0.0078883	-0.0126215
95%	-0.0240125	-0.0134170	-0.0181457
99%	-0.0393473	-0.0249651	-0.0300397

Table 13 Failure Test Probability Results for VaR Values of Apples Using the TGARCH Model.

Confidence Level (c)	Failure Count (N)	Standard Count (T)	Failure Rate (N/T)	Standard Failure Rate (P*)	LR Value
90%	6	105	5.71%	10%	2.4955736
95%	1	105	0.95%	5%	5.3621032
99%	0	105	0%	1%	2.1105705

Based on Table 8 to 13, it can be concluded that the GARCH family models have strong volatility forecasting capabilities for apples in this study. At the 90%, 95%, and 99% confidence levels, the failure rate is lower than the standard failure rate. At the 99% confidence level, the failure rate reaches 0%. This indicates that the models can effectively improve the reliability of risk prediction. This has significant implications for risk management of apples, as it helps optimize resource allocation, develop hedging strategies, and reduce risk costs.

4.2.1 Banana

Use EViews to establish the GARCH, GARCH-M, and TGARCH models, and calculate and backtest the Value at Risk (VaR) for grapes.

Table 14 VaR Values for Grapes Using the GARCH Model at Different Confidence Levels.

Confidence Level	VaR Minimum Value	VaR Maximum Value	VaR Average Value
90%	-0.0476838	-0.0032339	-0.0217677
95%	-0.0572143	-0.0121548	-0.0298154
99%	-0.0767992	-0.0304871	-0.0463531

Table 15 Failure Test Probability Results for VaR Values of Grapes Using the GARCH Model.

Confidence Level (c)	Failure Count (N)	Standard Count (T)	Failure Rate (N/T)	Standard Failure Rate (P*)	LR Value
90%	5	105	4.76%	10%	3.8946968
95%	1	105	0.95%	5%	5.3621032
99%	0	105	0%	1%	2.1105705

Table 16 VaR Values for Grapes Using the GARCH-M Model at Different Confidence Levels.

Confidence Level	VaR Minimum Value	VaR Maximum Value	VaR Average Value
90%	-0.0407091	0.0038044	-0.0199185
95%	-0.0513877	-0.0066767	-0.0287122
99%	-0.0730176	-0.0269605	-0.0465242

Table 17 Failure Test Probability Results for VaR Values of Grapes Using the GARCH-M Model.

Confidence Level (c)	Failure Count (N)	Standard Count (T)	Failure Rate (N/T)	Standard Failure Rate (P*)	LR Value
90%	7	105	6.67%	10%	1.4515467
95%	2	105	1.90%	5%	2.7444345
99%	0	105	0%	1%	2.1105705

Table 18 VaR Values for Grapes Using the TGARCH Model at Different Confidence Levels.

Confidence Level	VaR Minimum Value	VaR Maximum Value	VaR Average Value
90%	-0.0462745	-0.0052668	-0.0214882
95%	-0.0553221	-0.0147540	-0.0293979
99%	-0.0737571	-0.0283294	-0.0455146

Table 19 Failure Test Probability Results for VaR Values of Grapes Using the TGARCH Model.

Confidence Level (c)	Failure Count (N)	Standard Count (T)	Failure Rate (N/T)	Standard Failure Rate (P*)	LR Value
90%	5	105	4.76%	10%	3.8946968
95%	2	105	1.9%	5%	2.7444345
99%	0	105	0%	1%	2.1105705

From Table 14 to 19, it can be observed that the GARCH family models demonstrate excellent volatility forecasting capabilities for grapes in this study. At the 90%, 95%, and 99% confidence levels, the failure rates are all below the standard failure rates. At the 99% confidence level, the failure rate is 0%. This indicates that the models can effectively enhance the reliability of risk prediction. This has significant implications for grape risk management, helping to optimize resource allocation, develop hedging strategies, and reduce risk costs.

5. Research Conclusions and Recommendations

5.1 Research Conclusions

This study investigates the price fluctuations of three types of fruits through quantitative and qualitative approaches. Using GARCH family models, it analyzes the volatility characteristics of different fruits and applies Value at Risk (VaR) calculations and backtesting to manage the risks associated with fruit prices. The key findings are as follows:

(1) Price Volatility and Distribution:

Fruit prices, as special assets, exhibit high volatility and heavy-tailed distributions. The log returns of apple, banana, and grape prices from January 31, 2014, to January 19, 2024, are used to reflect price fluctuations. The samples pass normality and stationarity tests but show autocorrelation. ARMA(1,1) models are constructed for apples and grapes to eliminate autocorrelation, and ARCH-lm tests confirm the presence of conditional heteroscedasticity. Thus, GARCH family models are suitable for these fruits. However, banana prices do not show significant conditional heteroscedasticity, making GARCH family models unsuitable for bananas.

(2) Model Comparison and Parameter Estimation

By establishing three types of GARCH models and estimating parameters under normal, Student's t, and GED distributions, it is found that the models perform best under the GED distribution (with the lowest AIC and BIC). The sum of GARCH terms for apples and grapes is significant and less than 1, indicating the persistent impact of price shocks. In the GARCH-M model, apples do not show a high-risk, high-return characteristic, while grapes exhibit such a pattern. In the TGARCH model, apples show no asymmetric effects, whereas grapes exhibit significant asymmetry.

(3) VaR Analysis and Backtesting

Under the GED distribution, GARCH, GARCH-M, and TGARCH models are built for the log returns of apples and grapes. VaR values at different confidence levels are calculated, with the maximum, minimum, and average values recorded. A negative correlation is observed between risk values and confidence levels. At the 90%, 95%, and 99% confidence levels, failure rates are below the standard failure rates. At the 99% confidence level, the failure rate is 0%. This demonstrates the reliability of the models in improving risk prediction accuracy. These findings are significant for fruit risk management, aiding in resource optimization, hedging strategies, and reducing risk costs.

5.2 Recommendations

(1) Optimize Risk Management Strategies

For fruits with high price volatility, such as apples and grapes, it is recommended to adopt GARCH model-based risk management strategies. Assessing VaR values can help businesses and farmers better respond to price fluctuations and develop hedging strategies.

(2) Resource Allocation and Procurement Planning

Based on the volatility characteristics of different fruits—e.g., persistent price fluctuations for apples and high-risk, high-return patterns for grapes—businesses and farmers should adjust resource allocation and procurement plans flexibly to optimize capital efficiency.

(4) Further Study of External Risk Factors

Future research should incorporate external factors such as weather and pests into the analysis of fruit price fluctuations. Combining tools like insurance and futures markets can lead to more comprehensive risk management models.

(5) Enhance Policy Support and Information Sharing

Governments should establish supportive policies and create a shared fruit price data platform to improve market transparency. This would help stakeholders reduce risks stemming from information asymmetry.

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