Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development
Vol. 25, Issue 3, 2025
PRINT ISSN 2284-7995, E-ISSN 2285-3952

ANALYSIS OF COMPETITIVENESS AND VOLATILITY IN THE BENINESE COTTON MARKET

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Abstract

The objective of this research is to analyze the competitiveness and volatility of Benin's cotton export prices. The study utilizes monthly data covering the period from January 2010 to December 2023, collected from the FAO (Faostat) and the International Trade Centre (ITC) and analyzed using EViews 12 software. Competitiveness was assessed using the Revealed Comparative Advantage (RCA) and Net Export Index (NEI). Price volatility was examined through the ADF stationarity test and time series econometric models, specifically ARIMA, ARCH, and GARCH. The findings from the NEI and RCA indices indicate that Benin consistently exports more cotton than it imports and holds a substantial comparative advantage in this sector. In terms of price fluctuations, the GARCH(1,1) model, chosen according to statistical criteria, highlights notable and sustained volatility. Projections from this model suggest a rising trend in price volatility, pointing to an upcoming period of increased uncertainty in Benin's cotton export markets. These findings provide crucial insights for the development of economic and trade policies aimed at mitigating market risks, optimizing investments, and improving decision-making among stakeholders in the cotton sector.

Key words: *volatility, ARCH model, GARCH model, cotton, Benin*

INTRODUCTION

Cotton is one of the most widely produced raw materials in the world. In 2023, global cotton production exceeded 74 million tonnes, cultivated over more than 32 million hectares. The global average yield per hectare stood at over 2 thousand kilograms. In terms of production volume and cultivated area, the leading cotton-producing countries are China, India, the United States, Brazil, and Pakistan. However, the highest yields per hectare are recorded in China, Mexico, Turkey and Brazil [9]. In 2023, cotton production in Benin reached 597 thousand tonnes over a cultivated area of 508 thousand hectares, ranking the country 14th worldwide and 3rd in Africa, behind Burkina Faso and Mali. In 2010, national production was only 136 thousand tonnes over approximately 137 thousand hectares. Thus, between 2010 and 2023, Benin more than doubled both its cotton production and cultivated area, with a peak of 766 thousand tonnes recorded in 2021. However, the yield per hectare did not increase proportionally, rising from 1,000 kg/ha in 2010 to 1,176 kg/ha in 2023, representing only a 15% improvement [9]. The increase in cotton production in Benin has been primarily driven by the expansion of cultivated areas rather than improvements in yield per hectare. According to [10], several factors limit yield improvement in the country, including climatic variability, the absence of irrigation systems, high agricultural input costs, lack of mechanization, insufficient farmer training, and non-compliance with recommended agricultural practices. In contrast, countries such as China (6,635 kg/ha), Mexico (4,518 kg/ha), and Turkey (4,398 kg/ha) achieve significantly higher yields than the global average. While these countries have also expanded their cotton-growing areas, they have primarily focused on implementing efficient irrigation systems and adopting modern technologies to optimize cotton production [22].

Cotton is a central pillar of the economy for many countries, serving as a crucial source of employment and wealth creation in both rural and urban areas. In Benin, cotton accounts for nearly 50% of export revenues (excluding re-exports) and represents 45% of fiscal revenues (excluding customs duties). Additionally, it provides a livelihood for approximately one-third of the population and constitutes 60% of the physical capital in Benin's industrial sector, where it generates over 3 thousand paid jobs [10]. Despite these benefits for various stakeholders in the cotton industry, fluctuations in global cotton prices can have significant repercussions across the entire value chain. According to [22], the primary determinants of cotton price volatility include production volumes and stock levels in major producing nations, particularly China and the United States, which dominate the global market. Moreover, the production and pricing of alternative textile fibers, such as wool, mohair, and synthetic fibers, also influence cotton price formation. Ultimately, the exchange rate of the U.S. dollar against other currencies significantly influences these price variations.

In existing research, several econometric approaches, including ARCH, GARCH, and EGARCH models, have been utilized to analyze market price volatility. The use of ARCH-GARCH models for volatility analysis is justified by the limitations of linear models, which struggle to accurately model time series that do not follow a normal distribution. In 1982, Engle introduced the ARCH(q) model, where q denotes the number of past periods taken into account, to capture the changing variance of error terms over time [23]. This model posits that the variance at a given moment is influenced by previous squared errors. Expanding on this concept, Bollerslev developed the GARCH(p, q) model in 1986, which enhances the ARCH framework by incorporating both past squared errors and the conditional variance of prior errors, along with the latest volatility dynamics [23, 7].

By employing both symmetric and asymmetric models from the GARCH family, [7] analyzed the volatility characteristics of the Jordanian financial market. The study found that symmetric ARCH and GARCH models effectively captured volatility clustering and leptokurtosis in the Amman Stock Exchange. However, the EGARCH model did not provide evidence of a leverage effect in stock returns. In Turkey, [18] investigated sugar price fluctuations and determined that the GARCH(1,1) model was the most appropriate for modeling price volatility. Moreover, [17] examined the short- and long-term effects of cotton price volatility in Turkey using an asymmetric BEKK-GARCH model with a mean equation. Their results indicated significant volatility in the cotton market, with persistent uncertainty also impacting the maize market.

In Benin, multiple studies have explored agricultural price volatility, including [15], who analyzed the price fluctuations of dried chili peppers across major markets in the country. Using the ARCH model, the study confirmed the presence of significant price volatility across all analyzed markets. Similarly, [12] assessed the impact of the food reserve program on rice price fluctuations using an EGARCH model. Their findings indicated that the program failed to reduce price volatility. When prices were low, stockholders tended to sell more, thereby reducing available stocks for the following period and intensifying future volatility. Conversely, higher prices encouraged stock retention, which in turn limited volatility. In another study, [1] examined how maize producers respond to price volatility. Their findings suggested that farmers increased production and cultivated areas as a strategy to mitigate price instability, ensuring a minimum income despite market fluctuations. Furthermore, [16], using an ARCH-M model, investigated the impact of climatic factors on maize price volatility in Benin. Their study concluded that rainfall and temperature negatively influenced maize price volatility.

Despite the existing literature, few studies have specifically examined the volatility of Benin's cotton export prices.

This research aims to fill this gap by analyzing the competitiveness and volatility of cotton export prices in Benin. The findings will provide policy recommendations to reduce the country's vulnerability in international markets.

Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development
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PRINT ISSN 2284-7995, E-ISSN 2285-3952

MATERIALS AND METHODS

This research relies on secondary data from FAO (production, cultivated area, and yield) and ITC (imports and exports) covering the period 2010–2023. The volatility analysis was conducted using monthly export prices recorded between January 2010 and December 2023. To carry out this study, both descriptive and quantitative analytical approaches were employed. The descriptive approach facilitated the analysis of statistical indicators such as the mean, skewness coefficient, and kurtosis coefficient. Meanwhile, the quantitative approach was used to examine price volatility through the ARCH-GARCH model, utilizing EViews 12 software.

To assess competitiveness, the Revealed Comparative Advantage (RCA) indicator, proposed by Balassa, was calculated. This indicator is determined for a specific commodity in this case, cotton by computing the ratio between the share of this commodity in a country's total exports and its share in global exports. For a given country i and commodity j, the formula is as follows [3]:

$$RCA= (x_j^i/\sum x^i) / (\sum x_j^k / \sum x^k) \quad (1)$$

x_j^i : export value of commodity *j* (cotton) in country *i* ; $\sum x^i$: sum of all export values in country *i* ; $\sum x_j^k$: sum of all export values of commodity *j* in the world; $\sum x^k$: sum of all export values in the world.

When the RCA value is below 1, it indicates that the country lacks a revealed comparative advantage for the product. On the other hand, an RCA greater than 1 suggests that the country holds a revealed comparative advantage in that product. Furthermore, the Net Export Index (NEI) was employed to assess whether Benin functions as a net exporter or importer of cotton. The NEI is calculated as the ratio between the difference in exports and imports of cotton and its total trade (exports + imports) [4].

$$NEI_{ij} = (X_{ij} - M_{ij}) / (X_{ij} + M_{ij}) \quad (2)$$

In equation (2), X: exports, M: imports, j: product (cotton), i: country considered.

The index ranges between [-1; 1]. A NEI value close to -1 indicates that a country is primarily an importer, whereas a NEI value close to 1 suggests that the country is predominantly an exporter.

To analyze volatility in this study, the ARCH-GARCH method was applied through a multi-step process. To ensure data stationarity and enhance the effectiveness of ARCH-GARCH models in capturing volatility dynamics, the raw time series of monthly cotton export prices was transformed into logarithmic returns. This transformation is defined by the following equation:

$$returns = d(\log Prx) \quad (3)$$

where Prx represents the raw price series. The use of returns rather than raw prices is justified by several factors. Logarithmic returns facilitate statistical analysis, improve comparability, yield more normally distributed data, enhance stationarity, and allow for more efficient modeling [8].

The first step involved verifying the stationarity of the return series, as ARCH-GARCH models require stationary data. The Augmented Dickey-Fuller (ADF) test was conducted to check for unit roots [13]. After confirming stationarity, the next phase focused on identifying conditional heteroscedasticity by testing for the presence of the ARCH effect in the residuals. However, before conducting this test, an ARMA or ARIMA model was fitted to capture the structure of returns. The optimal model was selected based on several criteria, including the minimum values of the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), as well as higher values of Adjusted R^2 and Log-Likelihood [21, 24].

Next, the ARCH-LM (Lagrange Multiplier) test was performed to determine whether the variance of residuals depends on past values [23]. The null hypothesis assumes no ARCH effect, while the alternative hypothesis suggests its presence. If the p-value is below 5%, the null hypothesis is rejected, confirming the existence of the ARCH effect. Once detected, an ARCH(q) model can be applied, which is formulated as follows [23, 7]:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (4)$$

Where σ_t^2 is the conditional variance, α_0 and α_i are positive parameters, q is the model order, ε_t is the error term, and the sum $\sum \alpha_i$ must be less than 1 to ensure model stability.

If the ARCH(q) model exhibits instability, a GARCH(p, q) model is employed to improve volatility modeling. The GARCH(p, q) model is defined as follows [23, 7]:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \varepsilon_{t-j}^2 \quad (5)$$

Where β_j represents coefficients measuring the impact of past variances, and p is the GARCH order (i.e., the number of past variances considered). The sum $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j$ must be positive and less than 1.

Once the GARCH models were estimated, their performance was evaluated based on several criteria, including: sign and significance of coefficients, model stability, Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values.

The optimal model was the one with the highest Log-Likelihood value and the lowest AIC and SC values. Subsequently, a reassessment was conducted to verify whether the residual ARCH effect had been eliminated.

Finally, the residuals of the selected model were examined to ensure they were white noise, meaning they exhibited no autocorrelation [14].

RESULTS AND DISCUSSIONS

Competitiveness analysis

Over the past decade, the quantity and value of global cotton exports have increased significantly.

Between 2010 and 2023, the export volume increased from 6 million to over 8 million tons, while the export value doubled, rising from $8 billion to over $16 billion [11].

In 2023, the leading cotton-exporting countries were the United States, Brazil, and Australia. Benin ranked 6th globally, exporting over 239 thousand tons and generating more than $504 million in revenue [11].

Compared to some of its West African neighbors, Benin recorded a relatively high export volume.

For instance, Burkina Faso exported 127 thousand tons of cotton in 2023, generating $255 million, while Côte d'Ivoire exported over 92 thousand tons, valued at $203 million.

Overall, the value and volume of global cotton imports have declined in recent years. Between 2010 and 2023, the imported quantity dropped from 8 to 6 million tons, while the import value slightly decreased from $16 billion to $15 billion.

In 2023, the leading cotton-importing countries were China, Vietnam, and Bangladesh [11].

Benin, like many other African nations, imports almost no cotton. The Net Export Index (NEI = 1) confirms that Benin remained a net exporter of cotton throughout the 2010–2023 period (Table 1).

This result indicates that cotton imports into Benin have not yet significantly developed. Although the country has textile processing units, it continues to prioritize exports to generate foreign exchange earnings.

The Revealed Comparative Advantage (RCA) analysis shows that Benin has a significant comparative advantage (Table 1).

The average RCA between 2010 and 2023 for Benin, Burkina Faso, and Côte d'Ivoire was 522.50, 142.76, and 23.75, respectively.

These findings are consistent with [20], who previously highlighted Benin's strong comparative advantage in cotton production. However, having a comparative advantage does not eliminate sectoral risks.

Analyzing the volatility of export prices remains crucial, even in the presence of a high comparative advantage.

Table 1. RCA and NEI results

	Benin	Burkina-Faso	Côte d'Ivoire
	RCA		
2010	206.679	171.580	12.148
2015	589.919	181.376	26.352
2020	646.098	72.482	27.900
2021	725.825	106.986	33.087
2022	727.343	114.265	25.734
2023	677.019	80.837	15.682
Total Average	522.503	142.760	23.745
	NEI		
Total Average	1	1	1

Source: Authors' calculations.

Cotton Export Price Volatility Index Benin

The analysis of the raw export price graph reveals an irregular trend, characterized by fluctuations alternating between increases and decreases (Figure 1). These variations are primarily driven by the dynamics of supply and demand in the international cotton market [22]. The low yields, which are below the global average due to various constraints, limit Benin's capacity to supply large quantities of cotton to the global market [10]. Furthermore, export price fluctuations may also be attributed to the quality of Beninese cotton: the lower the quality, the lower the selling price [22].

Fig. 1. Graph of Raw Export Price and Logarithmic Return of Cotton Exports (2010–2023)
Source: Authors' calculations.

However, the main variable analyzed in this study is not the raw price but rather the logarithmic return. The examination of the graph suggests that the logarithmic return appears stationary (though confirmation through the Augmented Dickey-Fuller (ADF) test is required) and that its mean fluctuates around zero.

Figure 2 presents the key descriptive statistics of the return series. The analysis reveals a mean return of 0.12% and a standard deviation of 0.14%. While the mean return is slightly positive, the relatively high standard deviation indicates significant fluctuations around this average, reflecting high volatility and market uncertainty. The skewness coefficient is positive and greater than zero (0.367 > 0), indicating a right-skewed distribution. In other words, extreme positive returns occur more frequently than extreme losses. Additionally, the kurtosis coefficient is greater than 3 (6.550 > 3), indicating a leptokurtic distribution. This suggests the presence of heavy tails, meaning a higher number of extreme observations compared to a normal distribution (Figure 2). A high Jarque-Bera (JB) statistic (JB = 91.407) suggests a significant deviation from normality. Since the associated probability is less than 5% (0.000 < 0.05), the null hypothesis (H0), which assumes a normal distribution, is rejected. The values of the skewness and kurtosis coefficients confirm that the return distribution is non-normal. The presence of positive skewness and high kurtosis indicates extreme movements and non-constant volatility. To better capture this volatility dynamic, the use of an ARCH-GARCH model is deemed more appropriate. Similar findings have been reported in other studies [7, 2]. In their analyses of return series, the kurtosis statistic was also greater than 3, and the p-value of the Jarque-Bera (JB) test was below 5%, further confirming the non-normality of the distributions examined.

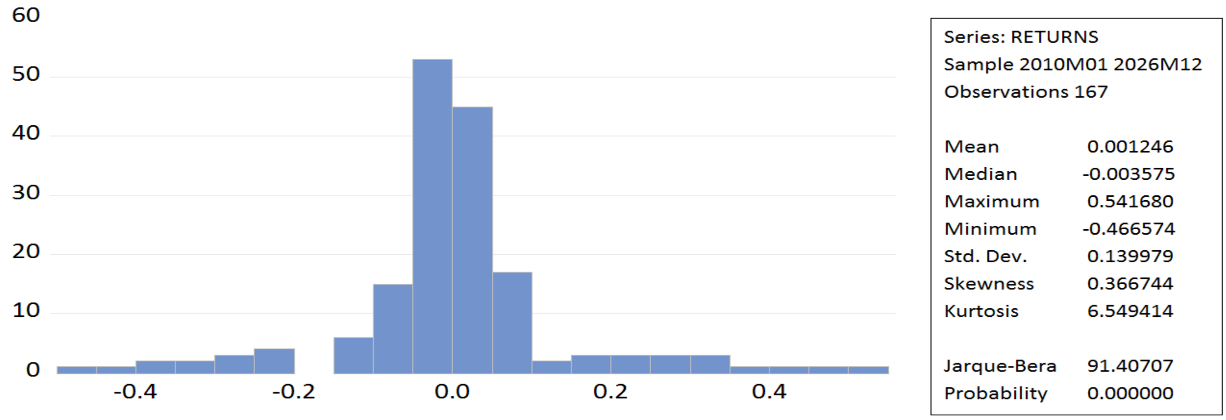


Fig. 2. Descriptive Statistics of the Return Series
Source: Authors' calculations.

Analysis of return series stationarity

For a time series to be used in a predictive model, it is essential that it be stationary. Statistical tests, particularly the Augmented Dickey-Fuller (ADF) test, can be used to assess stationarity. This test compares the computed statistic to a 5% critical value. If the test statistic is lower than this threshold, the null hypothesis is rejected in favor of the alternative hypothesis, which states that the series does not contain a unit root [8]. The analysis of Table 2 indicates that the return series is stationary at level and therefore does not require differencing. The probability associated with the test is below 5%, allowing for the rejection of the null hypothesis, which assumes the presence of a unit root in the series.

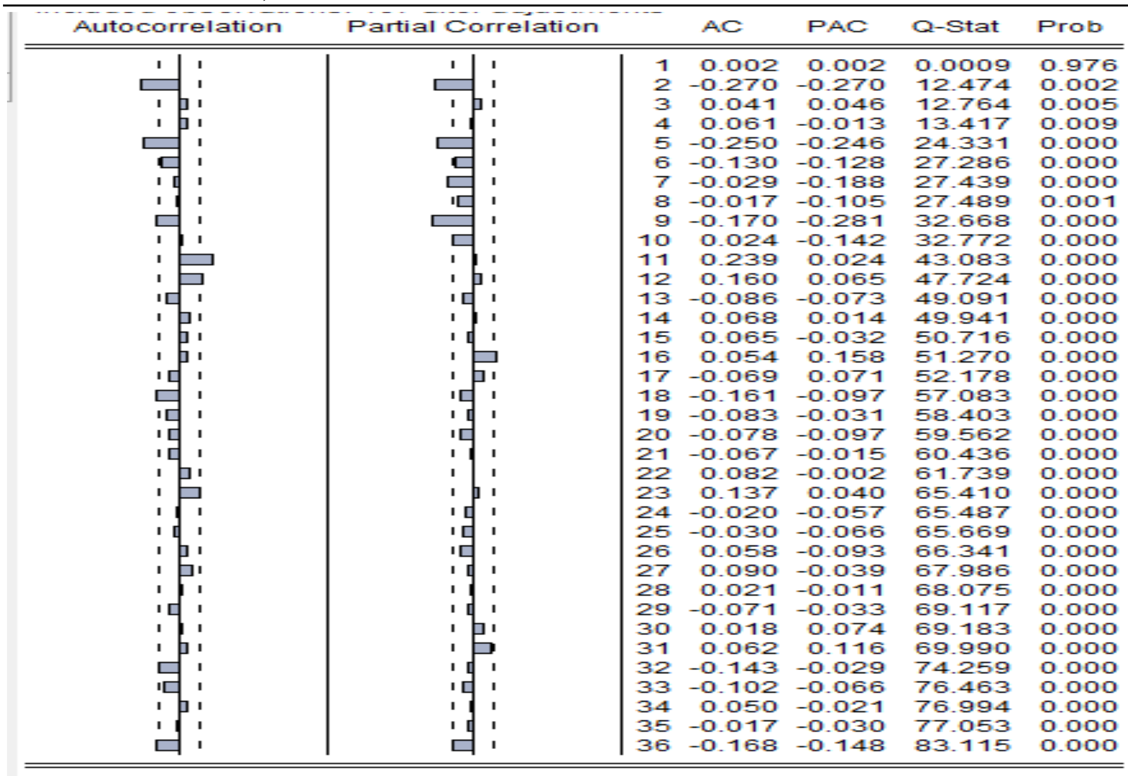
Table 2. ADF test results for the return series

	1%	5%	10%	ADF test	p-value
I(0)	-2.580	-1.942	-1.615	-8.850	0.000

Source: Authors' calculations.

ARMA model estimation

Since the return series is stationary at level, only the p and q components will be identified using the correlogram (Figure 3). The order of the autoregressive (p) component is determined by examining the partial autocorrelation function (PACF) column, while the order of the moving average (q) component is identified through the autocorrelation function (ACF) column. The optimal model is selected based on various criteria, such as the statistical significance of the autoregressive (AR) and moving average (MA) coefficients, the adjusted R^2, and the Log Likelihood value. Additionally, the Akaike Information Criterion (AIC), Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQ) should be minimized. The analysis of Table 3 indicates that the ARMA(5,2) model is the most appropriate, as its coefficients are significant, and it has the lowest values for the AIC, SC, and HQ criteria. These selection criteria have also been applied in numerous previous studies to identify the most suitable ARMA model [5, 24 19].



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.002	0.002	0.0009	0.976
		2	-0.270	-0.270	12.474	0.002
		3	0.041	0.046	12.764	0.005
		4	0.061	-0.013	13.417	0.009
		5	-0.250	-0.246	24.331	0.000
		6	-0.130	-0.128	27.286	0.000
		7	-0.029	-0.188	27.439	0.000
		8	-0.017	-0.105	27.489	0.001
		9	-0.170	-0.281	32.668	0.000
		10	0.024	-0.142	32.772	0.000
		11	0.239	0.024	43.083	0.000
		12	0.160	0.065	47.724	0.000
		13	-0.086	-0.073	49.091	0.000
		14	0.068	0.014	49.941	0.000
		15	0.065	-0.032	50.716	0.000
		16	0.054	0.158	51.270	0.000
		17	-0.069	0.071	52.178	0.000
		18	-0.161	-0.097	57.083	0.000
		19	-0.083	-0.031	58.403	0.000
		20	-0.078	-0.097	59.562	0.000
		21	-0.067	-0.015	60.436	0.000
		22	0.082	-0.002	61.739	0.000
		23	0.137	0.040	65.410	0.000
		24	-0.020	-0.057	65.487	0.000
		25	-0.030	-0.066	65.669	0.000
		26	0.058	-0.093	66.341	0.000
		27	0.090	-0.039	67.986	0.000
		28	0.021	-0.011	68.075	0.000
		29	-0.071	-0.033	69.117	0.000
		30	0.018	0.074	69.183	0.000
		31	0.062	0.116	69.990	0.000
		32	-0.143	-0.029	74.259	0.000
		33	-0.102	-0.066	76.463	0.000
		34	0.050	-0.021	76.994	0.000
		35	-0.017	-0.030	77.053	0.000
		36	-0.168	-0.148	83.115	0.000

Fig. 3. Level correlogram of the return series
Source: Authors' calculations.

Table 3. Characteristics of candidate ARMA models

ARMA	AR	MA	Adjusted R^2	Log Likelihood	AIC	SC	HQ
(2,2)	0.711	0.060	0.058	98.346	-1.130	-1.055	-1.100
(2,5)	0.000	0.001	0.132	104.989	-1.210	-1.135	-1.180
(5,2)	**0.000**	**0.000**	**0.155**	**107.021**	**-1.234**	**-1.159**	**-1.203**
(5,5)	0.626	0.656	0.048	97.327	-1.118	-1.043	-1.087
(9,2)	0.040	0.000	0.084	100.505	-1.156	-1.081	-1.125
(9,5)	0.053	0.002	0.073	99.462	-1.143	-1.069	-1.113

Source: Authors' calculations.

Detection of the ARCH Effect in Residuals

An ARCH test was conducted to verify the presence of heteroskedasticity in the previously estimated ARMA(5,2) model. The identification of this heteroskedasticity is based on the significance of the probability values associated with the F-statistic and the chi-square statistic at the 5% threshold [13]. The ARCH test detects this effect by testing the null hypothesis (H_0), which states that no ARCH effect exists. The results indicate that the ARMA(5,2) model exhibits an ARCH effect, as evidenced by the probability values of the F-statistic and chi-square statistic (0.0000 < 0.05) (Table 4). Consequently, a more in-depth analysis was conducted by applying an ARCH-GARCH model to better capture the volatility dynamics. Contrary to these findings, [17] highlighted the absence of an ARCH effect in the cotton return series in Turkey.

Table 4. ARCH test results

F-statistic	Obs*R-squared	Prob. F	Prob. Chi-Square
38.458	31.533	0.000	0.000

Source: Authors' calculations.

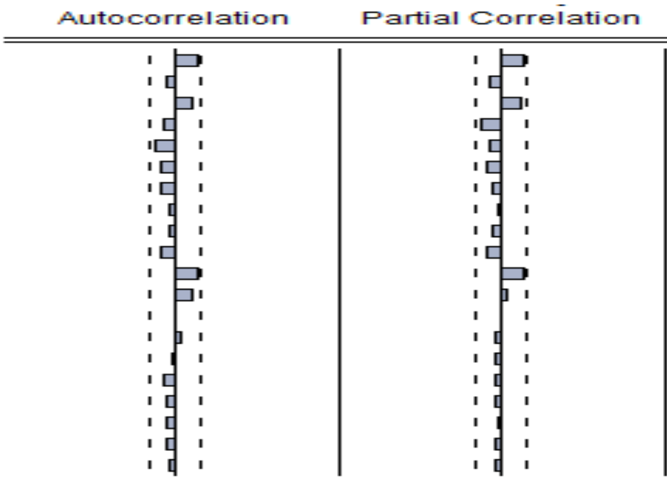
The examination of Table 5 indicates that the ARCH-GARCH(1,1) model has the lowest AIC and SC information criteria, along with the highest Log Likelihood value, supporting its selection. Furthermore, the ARCH-LM test was performed to assess whether the ARCH effect remains in the ARCH-GARCH(1,1) model. The probability values of the F-statistic (0.075) and chi-square statistic (0.074) exceed the 5% threshold, confirming the absence of heteroskedasticity in the chosen model. This suggests that the ARCH effect has been successfully removed from the analyzed series. These findings align with those of [2], who, after applying the ARCH-LM test, also confirmed the absence of an ARCH effect in their selected model for volatility analysis.

Table 5. ARCH-GARCH model test results

ARCH-GARCH	ARCH	GARCH	Log Likelihood	AIC	SC
ARCH-GARCH (1,0)	1.002	-	134.657	-1.601	-1.505
ARCH-GARCH (1,1)	0.158	0.840	146.120	-1.730	-1.616
ARCH-GARCH (0,1)	-	0.222	103.519	-1.216	-1.121

Source: Authors' calculations.

To validate the ARCH-GARCH(1,1) model, the Ljung-Box test was employed to assess the independence of the squared residuals. As illustrated in Figure 4, which presents the autocorrelation of the squared standardized residuals, the obtained probability values exceed 5%. These findings suggest that the residuals are independent, confirming the model's adequacy.



	AC	PAC	Q-Stat	Prob*
1	0.141	0.141	3.2685	0.071
2	-0.055	-0.076	3.7663	0.152
3	0.107	0.130	5.6897	0.128
4	-0.073	-0.118	6.5777	0.160
5	-0.119	-0.074	8.9609	0.111
6	-0.086	-0.089	10.231	0.115
7	-0.092	-0.062	11.690	0.111
8	-0.039	-0.014	11.955	0.153
9	-0.045	-0.050	12.313	0.196
10	-0.086	-0.086	13.617	0.191
11	0.148	0.155	17.488	0.094
12	0.109	0.036	19.580	0.075
13	-0.003	-0.000	19.581	0.106
14	0.027	-0.030	19.710	0.140
15	-0.010	-0.034	19.729	0.183
16	-0.067	-0.044	20.551	0.196
17	-0.059	-0.032	21.197	0.218
18	-0.053	-0.024	21.707	0.245
19	-0.061	-0.042	22.391	0.265
20	-0.045	-0.036	22.763	0.301

Fig. 4. Correlogram of Standardized Residuals Squared
Source: Authors' calculations.

Results of the GARCH(1,1) Model

Table 6 presents the estimation results of an ARMA-GARCH model, which integrates both a mean equation and a conditional variance equation. The coefficients in the mean equation are negative but statistically significant at the 5% level. The variance equation, employing a GARCH(1,1) framework to model conditional volatility, captures the evolution of volatility over time in response to past shocks and previous volatility levels. The analysis of the conditional variance equation indicates that the coefficients of the GARCH(1,1) model are significant, validating its suitability. This suggests that the GARCH(1,1) model is appropriate for forecasting volatility. Additionally, the results show that volatility is persistent, with a GARCH(-1) coefficient of 0.840, and that past shocks have a strong impact on future volatility, as evidenced by RESID(-1)^2 = 0.158. This implies that following a market shock, volatility does not dissipate immediately but gradually declines over time.

From an economic perspective, this persistence in volatility increases uncertainty for producers in predicting their medium- and long-term revenues. Such uncertainty may hinder investment in modern equipment aimed at improving cotton production and exports, which could partially explain the low cotton yields in Benin. Moreover, if volatility remains high, it could weaken Benin's comparative advantage and reduce its global market share. According to [17], volatility in the cotton market is particularly high, and the resulting uncertainty affects not only the cotton sector but also other agricultural markets, such as maize. Additionally, external factors such as climate variability, exchange rate fluctuations, and global price volatility can further exacerbate instability in cotton export prices [22].

Table 6. GARCH(1,1) results Model

Mean Equation		
	Coefficient	Prob.
C	0.004	0.161
AR(2)	-0.251	0.006
MA(5)	-0.372	0.000
Variance Equation		
C	9.94E-05	0.028
RESID(-1)^2	0.158	0.001
GARCH(-1)	0.840	0.000

Source: Authors' calculations.

Forecasting Return Series and Variance

The longer the forecasting horizon, the greater the uncertainty in the data due to environmental and anthropogenic constraints [6]. Since volatility follows a stochastic process and future shocks (such as financial crises or geopolitical disruptions) are difficult to anticipate, this study avoids long-term forecasts. However, as part of this exploratory analysis, a volatility projection was conducted for the year 2026 (Figure 5).

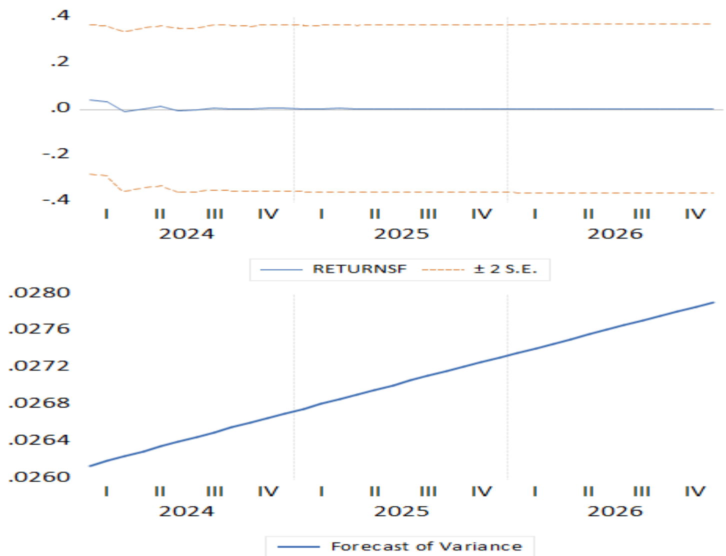


Fig. 5. Return series and volatility forecast plot
Source: Authors' calculations.

The analysis of the graph highlights an increase in the volatility of Benin's cotton export prices, indicating a period of heightened uncertainty in export markets in the coming years. This increased volatility could have significant economic, commercial, and strategic consequences. Indeed, instability in cotton export prices could weaken the sector, impact producers' incomes, and necessitate the implementation of price stabilization policies. In a scenario where prices experience a sudden drop, the impact on the trade balance could be substantial, leading to a reduction in export revenues and, consequently, a decline in foreign currency inflows. At the household level, farmers would face greater uncertainty regarding their earnings. According to [10], a 40% decrease in farm-gate cotton prices would lead to a 6–8% increase in rural poverty rates. From a macroeconomic perspective, a $1 decline in cotton producers' income would result in a $2.96 decrease in national income. Given these considerations, it becomes imperative to adopt appropriate strategies to mitigate the adverse effects of this foreseeable volatility and to strengthen the resilience of the sector.

CONCLUSIONS

This study analyzed the competitiveness and volatility of the cotton market in Benin. The findings highlighted that Benin is a net exporter of cotton and enjoys a high comparative advantage in this agricultural commodity. However, a strong comparative advantage does not necessarily ensure stability in export prices. To assess price stability, an analysis of the monthly export price return series was conducted. The results revealed non-constant volatility, characterized by positive skewness (Skewness > 0) and a leptokurtic distribution (Kurtosis > 3). To capture this volatility dynamic, a GARCH model was estimated. Before estimating the GARCH model, an ARMA(5,2) model was selected to specify the mean equation, based on statistical criteria that identified the most suitable model among several candidates. The estimation of the GARCH(1,1) model allowed for the modeling of conditional volatility through the variance equation. The results indicate that volatility is persistent and that periods of high volatility tend to last before gradually dissipating. A short-term forecast suggests that this volatility will remain elevated in the coming years.

Based on these findings, several recommendations have been formulated. Given the anticipated increase in volatility, the government could consider implementing stabilization funds or support policies for producers to mitigate the impact of price fluctuations. The adoption of agricultural contract services could also help protect farmers' incomes against price shocks. Furthermore, the government could explore new market opportunities and strengthen existing trade agreements to reduce the country's dependence on a limited number of major buyers.

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