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ASYMMETRIC BEHAVIOR IN THE FOOD INDUSTRY: EVIDENCE FROM STOXX EUROPE 600 FOOD PRICE INDEX.

Tarana AZIMOVA[1]

Abstract

The study uses univariate asymmetric GARCH models to model and forecast the cyclical nature of food and agricultural stock index price returns. Particularly, this article employs the EGARCH and GJR-GARCH methodologies to examine changes in the STOXX Europe 600 food price index from September 24, 2012 to June 3, 2024. The study period was determined according to the availability of reliable data. The findings indicate volatility clustering with the ARCH effect in index return residuals. I observe that volatility surprises have a significant long-term effect on index returns. The findings show that there is a leverage effect on the food index series and that the effects of the shocks are asymmetric. This condition can be considered an overreaction anomaly and can lead to a mispricing of the index. Market participants may use trading strategies to generate abnormal returns. However, the overreaction anomaly is not evidence of inefficiency in European food and beverage market, unless the trading strategy based on the abnormal rewards is inconsistent and disappears once arbitraged away, with pricing eventually correcting itself. I emphasize that the negative market innovations lead to longer negative cycles before the food price converges towards its trend value.

Keyword: STOXX Europe 600 food price index, food industry, volatility shocks, leverage effect, negative cycles.
JEL codes: G11, Q14, C55, C58

GIDA ENDÜSTRİSİNDE ASIMETRIK OYNAKLIK: STOXX EUROPE 600 GIDA FIYAT ENDEKSİ ÜZERİNE BİR İNCELEME

Özet

Bu çalışma, tek değişkenli asimetrik GARCH modellerini kullanarak gıda ve tarım hisse senedi endeksi fiyat getirilerinin oynaklığını modellemekte ve tahmin etmektedir. Özellikle, bu çalışmada EGARCH ve GJR-GARCH metodolojileri kullanılarak 24 Eylül 2012 - 3 Haziran 2024 dönemi için STOXX Europe 600 gıda fiyat endeksindeki değişimler analiz edilmiştir. Sonuçlar, endeks getirilerinin kalıntılarında ARCH etkisiyle birlikte oynaklık kümelenmesi olduğunu göstermektedir. Oynaklık şoklarının endeks getirileri üzerinde kalıcı ve önemli bir etkisi olmaktadır. Bulgular, gıda endeksi serisinde bir kaldıraç etkisi olduğunu ve şokların etkilerinin asimetrik olduğunu göstermektedir. Bu durum, aşırı tepki anomalisi olarak değerlendirilebilir ve endeksin yanlış fiyatlanmasına yol açabilir. Piyasa katılımcıları, anormal getiriler elde etmek için ticaret stratejileri kullanabilir. Ancak, aşırı tepki anomalisi, anormal getiriler üzerine kurulu ticaret stratejilerinin tutarsız olması ve arbitraj yoluyla ortadan kalkması durumunda, fiyatlamanın nihayetinde düzelmesiyle Avrupa gıda ve içecek piyasasında bir verimsizlik kanıtı olarak kabul edilmez. Çalışma, negatif piyasa yeniliklerinin, gıda fiyatının trend değerine yakınsamadan önce daha uzun negatif döngülere yol açtığı vurgulanmaktadır.

Anahtar Kelimeler: STOXX Europe 600 gıda fiyat endeksi, gıda endüstrisi, oynaklık şokları, kaldıraç etkisi, negatif döngüler.
JEL kodlar: G11, Q14, C55, C58

[1] Assistant Prof. Dr. Istanbul Aydin University, e-mail teraneazimli@gmail.com , taranaazimova@aydin.edu.tr, ORCID: 0000-0001-6951-5844

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1. Introduction

Food is a strategic commodity and the main driving force behind the industrial and economic development of nations. The magnitude of price fluctuations and the likelihood of significant, unforeseen price spikes in the food market in recent decades increased price volatility in this industry. As food prices change, operating earnings in the food industry display potential variability. According to Labys et al. (2000), while favorable price fluctuations increased revenue from exports and domestic growth in income, adverse price movements reduced income growth and halted investment applications. Ginn (2023) notes that price fluctuations in agriculture has the largest effect on aggregate price swings, which may explain the destabilizing nature of food costs instability in many nations. Since the beginning of the century, price indices for food commodities worldwide have repeatedly experienced large real swings; this period is known as the supercycle. (Erten et al. (2021)). The present scenario affects the share returns of companies operating in the food industry. All participants in the agricultural markets are concerned about the risk of extreme price innovations, as this risk can affect human development and its security. Rezitis et al. (2013) use the structural trend approach to report seasonality, cyclicality, and high volatility in the monthly IMF food index return. Short-term cycles in the pricing of primary staple items such as maize, rice, wheat, and tea are studied by Labys et al. (2000). According to the author, while more immediate price movements have triggered revenues and balance-of-payments turbulence, a longer lasting price shifts in their downward stages contributed to secular shrinks in product conditions for trade. Headey et al. (2010) confirm that the price formation of agricultural commodities on the international market is a complicated process, as it is the result of complex interactions between demand, supply, actual prices, and price expectations. These complex interactions make it difficult to understand the precise reasons behind price spikes and the severity of their effects. However, understanding volatility in food markets is important for several reasons. Firstly, price swings have an economic impact on the company and influence the company's capital structure as well as its liquidity, current, equity and leverage ratios. The risk associated with the operating cost structure, particularly the use of fixed costs in operations- also known as leverage- is one of the main determinants that causes variability in operating earnings. Financial fixed costs generate financial leverage, and operating fixed costs generate operating leverage. Leverage can create upward and downward swings in returns. The degree of price fluctuations can serve as an important signal and help market participants to assess the quality of management' decisions for a listed food companies with the vision to be able to retain the advantage of being listed in

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stock exchange markets. Volatility is a crucial factor in assessing the risk and return profile of food companies, especially in cyclical industries like the food sector. Specifically, understanding how to analyze fluctuations in food returns is essential for determining the expected return threshold and estimating the present value of future incremental cash flows for a food company. With increasing globalization, there is concern that volatility in the food market could spill over into commodity markets and cause significant disruption in those markets. It is therefore important to analyze the dynamics of the food market in order to develop precise strategies and implement the necessary measures for sustainable agricultural. The cyclical pattern technique of Koopman et.al. (2000) is used to more fully comprehend the development of food index prices. The approach divides commodity food price series into multiple local criteria, such as patterns, seasonality, and cyclicality, as well as exogenous parameters like irregularities and interventions, which are represented by dummy variables. The pattern represents the long-lasting constant part of the data set and indicates the direction in which it is moving. The trend component takes into account changes in supply and demand that are permanent, along with changes in all undetectable elements that are ongoing. The element of seasonality reflects the fact that the prices of agricultural goods are susceptible to seasonal fluctuations. In the present model, I aim to investigate the dynamics of the food system of main European countries by using models of the GARCH family to investigate the behavior of the daily index between 2012 and 2024.

Roughly 90% of the European stock market's capitalization based on freely traded shares is represented by the 600 fixed components that make up the STOXX Europe 600, which incorporates small, medium and large capitalization enterprises from 17 European nations. The index comprises companies from various European regions, including Nordic countries like Sweden, Norway, Denmark, and Finland; Western European nations such as Belgium, the Netherlands, Luxembourg, and Ireland; as well as Southern and Central European countries including Italy, Spain, Portugal, Austria, and Poland. The United Kingdom makes up approximately 22.3% of the index, followed by France (16.6%), Germany (14.1%), Switzerland (14.9%), and Austria (11.1%). In this study I focus on the STOXX Europe 600 food and beverage index as the representative of food market. STOXX food and beverage index is a young and fast growing index including important companies such as DIAGEO(UK) with the market weight of 14.937%, followed by NESTLE (Switzerland), ANHEUSER-BUSCH INBEV (Belgium) and DANONE (France) with the weights of 14.353%, 13.085% and 9.816% respectively. The food and beverage index represents about 10 percent of the STOXX Europe

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600 index. Followed by STOXX Europe 600 oil and gas index with the average return of 25.91% in 2023, an annual average return of 23.59% is the second highest for STOXX on food and beverage index. These statistics compares to STOXX Europe 600 Basic Resources, Health Care, Banks and Automobiles with the average yearly returns of 23.39%, 21.09%, 20.75%, and 14.07% respectively. Current calculations put the market capitalization of STOXX Europe 600 index at 12,368.6 Billion and STOXX food and beverage index at $937.1 Billion for 2023. This data accentuates the importance of the food industry in the economies of European countries and it is highly appropriate to give the food industry more attention. I test the dynamics of Stoxx Europe 600 Food and Beverage index and compare the estimates using the conditional variance in the nonlinear structures. Assuming that the nonlinearity in food return series is a result of conditional variances, I model series using Engle's (1982) autoregressive conditional heteroscedasticity models. Specifically use the GARCH models and its extensions to broaden our understanding of the persistence and asymmetric nature of the index returns.

The manuscript's remaining sections are arranged in the following order. The theoretical background is given in the second part, the methods employed are outlined in the third part, the outcomes of all models are presented in section four, and the summary is provided in the last part.

2. Literature Review

Understanding the dynamics of stock returns is a topic of continuous investigation in financial market literature. Specifically, understanding the dynamics of price fluctuations in food markets is crucial for market participants, investors and decision makers. Although there is much theoretical and empirical work on volatility modelling of various markets, the volatility structure of the STOXX Food and Beverage has not been adequately studied to date. Headey et al. (2010) confirm that the pricing of food on the international market is a complicated process, as it is the result of complex interactions between demand, supply, actual prices and price expectations. These complex relationships make it difficult to determine the exact reasons for price spikes and the severity of their impact. The price of fuel is thought to be a major influence on the evolution of food prices. Rezitis et al.(2013) include two exogenous variables in the structural trend methodology, namely the real effective exchange rate of US and crude oil and report seasonality and cyclicality in the food index. The author explains the use of petroleum price by the fact that its increases production costs.

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The increase in food costs occurred amid a widespread increase in the prices of commodity, with metals and energy leading the way. However, during the financial crisis in 2008, the cost of a barrel of petroleum fell from 145 US dollars to 40 US dollars. Food prices decreased in tandem with these changes, though they have since made a partial recovery. Against this backdrop, many studies have attempted to establish the causality between fuel and food prices. Rosegrant et al. (2008), Filip et al. (2019), Dayong et al. (2020), Umar et al.(2021), Adeosun et. al.(2023), Sun et. al.(2023) contend that there is an apparent trade-off between "food" and "energy". Rosegrant et al. (2008) show that the conversion of food crops and, more broadly, agricultural land for the production of feedstock for biofuels drives up food prices and that fluctuations in food prices correlate with changes in the price of crude oil. Dayong et al. (2020) point to a significant shift in the level of interdependence in commodity prices worldwide following the financial meltdown of 2008. They demonstrate that the interdependence in swings in prices across seven essential merchandise classes increased from a mean of 14.82% prior to the crisis to an exceptionally high mean of 47.87% in the years that followed, a trend that continues to this day. Dayong et al. (2020) highlight a significant shift in the nature of connectedness in global commodity prices after the 2008 global financial crisis. They show that the co-dependence in price fluctuations across seven major commodity classes rose from an average of 14.82% before the crisis to an exceptionally high average of 47.87% in the years that followed, a trend that persists to the present day.

Umar et al.(2021) found that there is a bidirectional causality between fuel prices, and agricultural prices, and that there is an increase in connectivity during the period of the financial crisis. However, not all studies report a strong dependency between agriculture and energy. According to Baffes (2007), 17% of oil price changes are passed on to the prices of agricultural products. According to Mitchell (2008), higher energy and transportation costs would lead to in a 15–20% increase in agricultural production costs in the US. Yoon (2022) article. Using the quantile approach, the author found no cointegration between the quantiles of petroleum, ethanol, and corn prices.

Extensive research has been conducted on the interactions between food prices and economic variables. The majority of these studies have demonstrated the substantial effects of changes in food prices on economic activity in a number of developed and developing nations Ridler et al. (1972), Jebabli et al. (2014), Mawejje (2016), Gilbert (2010), Adeosun et al.(2023), Ginn (2023), Adjemian et al. (2024). Rezitis et al. (2013) include the real effective US exchange rate in their analysis of the seasonality and cyclicality of the food price index. According to the

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author, they include this variable because the US dollar used for the majority of foreign trade in goods. Ridler (1972) discovered that the prices of commodities—whether mineral or agricultural—are overly susceptible to changes in exchange rates. One explanation for this could be that the available demand-side variables do not adequately capture the cyclical component of both commodity price movements and exchange rates. Mawejje (2016) demonstrates that the primary drivers of price uncertainty are supply and demand. In contrast, Gilbert (2010) and Jebabli et al. (2014) contend that fluctuations in the exchange rates, interest rates and money supply are the main factors driving increases in food prices. Specifically, Gilbert (2010) emphasizes that markets are interlinked and that common demand-side variables, both monetary and macroeconomic, should be considered as the leading contenders for explaining significant fluctuations in the overall price of agricultural food. The author argues that index-based investments in agricultural futures markets were probably the primary channel for the monetary and macroeconomic forces responsible for the increases in food prices in 2007 and 2008. Adjemian et al. (2024) point out that the relationship between prices in different markets can be affected by macroeconomic fluctuations, suggesting that in times of financial and economic instability, the ability to predict prices based on information from a market may change. Wen et al. (2021) examine the symmetrical and asymmetrical outcomes of monetary policy uncertainty on the cost of groceries in China. Positive effects on food price volatility are outweighed by negative innovations in food prices, according to the results of the linear Autoregressive Distributive Lag framework. Sharma et al. (2006) emphasize that in food markets, where seasonality and supply constraints are prevalent the negative price shocks increase volatility more strongly than positive shocks. Recent studies emphasize that the pandemic period amplified food price fluctuations across different countries and commodity groups (Cardoso et al., 2021; Tetteh et al., 2021). There is no doubt that the academic literature has conducted detailed studies to find external causes and outliers of price volatility, but they have overlooked a crucial aspect, namely the nature of volatility and the asymmetric structure of the food market itself. Another clear limitation is that most studies consider semi-annual, monthly or weekly data. In order to explain price fluctuations and show the volatility patterns, it is important to use time series with daily returns. Furthermore, this paper complements the academic literature with its focus on modeling the volatility of the STOXX index. As far as I know, the volatility of the food and beverage STOXX index has not been studied before. I explain index price fluctuations with asymmetric univariate GARCH models over an prolonged period that includes the meltdown of 2008, the 2019 pandemic crisis and its aftermath.

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3. Material and Methods

Bollerslev (1986) added conditional heteroscedasticity to the moving average items in the ARCH and developed the GARCH (Generalized ARCH with Nonlinear Dynamics) tool. The unequal influence of upward and downward shocks on conditional variance or other forms of asymmetry are captured by GARCH techniques. In this specification, the conditional variance's own lag value is modelled as follows:

$$\sigma_t^2 = \mathrm{w}_0 + \sum_{i=1}^{f} \alpha_i \, u_{t-i}^2 + \sum_{j=1}^{t} \beta_j \sigma_{\mathrm{t-j}}^2 \qquad (1)$$

where, σ_t^2 is conditional variance, u_t is return residual and w_0, α_i, βj are factors to be forecasted.

Typical GARCH techniques assume that negative and positive error component affect volatility in a non-asymmetric way. However, for a variety of reasons, including transaction costs, market frictions, and arbitrage limits, financial time series actually display asymmetrical nonlinear patterns. This means that negative shocks or changes in the market tend to have a more prolonged impact on conditional volatility compared to equally sized positive shocks. This asymmetric pattern is not captured by the GARCH model. On the other hand, the EGARCH technique introduced by Nelson (1991) effectively captures the asymmetric effects of positive and negative news on the volatility of financial assets. The EGARCH model is formulated as follows:

$$ln(\sigma_t^2) = \omega + \beta \, ln(\sigma_{t-1}^2) - \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \qquad (2)$$

where γ stands for leverage effects, which explain the model's asymmetry. If γ<0, this means that negative market innovations cause more volatility than good news.

The GJR model, developed by Runkle et al. (1993), is an extension of the GARCH model that incorporates a variable to account for positive asymmetry, as shown below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \, u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \qquad (3)$$

where I_{t-1} is a dummy variable, dummy variable equals to 1 if u_{t-1}< 0 and equals to 0 if

u_{t-1}> 0.

where γ stands for leverage effects, which explain the model's asymmetry. If γ>0, this indicates on the presence of leverage effect.

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Given the objective of examining whether negative shocks exert stronger effects on volatility compared to positive shocks, these two specifications were considered both parsimonious and directly relevant.

4. Index Data and Empirical Results

4.1 Data

I utilize daily Stoxx Europe 600 Food and Beverage closing price data for the period of September 24, 2012 through June 03, 2024 to estimate the return variability of the food index.

The time frame under investigation was selected based on the accessibility and consistency of the available data. To enhance data quality and reduce noise, this manuscript applies daily mean statistics of Stoxx Europe 600 Food and Beverage. This index includes the largest European food companies including UK's DIAGEO, Switzerland's Nestle, Belgium's ANHEUSER-BUSCH INBEV and France DANONE listed on the Europe 600 Stock Market with the weights of 14.93%, 14.35%, 13.085% and 9.816 % respectively. I obtained the index data from Reuter's data terminal. I calculate the return by forming the fraction: the price at time t (pt) divided by the previous price (pt-1) and computing the exponential logarithm. The natural logarithmic price change that help to smooth the standard deviation and free it from heteroscedasticity.

$r_t = \ln(\frac{p_t}{p_{t-1}})$. Where r_t is the return data, p_t is the price on the day of the quotation and p_{t-1} is the price on the day before this quotation. The price and return graph pattern together with the preliminary statistical summary of the daily index under consideration is provided in Table 1. The 3000 return data statistics have a positive average (mean) value of 0.000153 and a risk value (standard deviation) of 0.009087. The negative skewness (-0.535217) reflects the asymmetric nature of the return series, aligning with the usual pattern seen in financial markets. The positive and high kurtosis of 9.954625 indicate that return time series are highly leptokurtic with regard to the normal distribution with a kurtosis value of exactly 3. Heavy tailed leptokurtic distribution imply that the Stoxx Europe 600 index carry more extreme positive or negative values. This condition increases the probability to experience exceptionally low or high returns and wider fluctuations.

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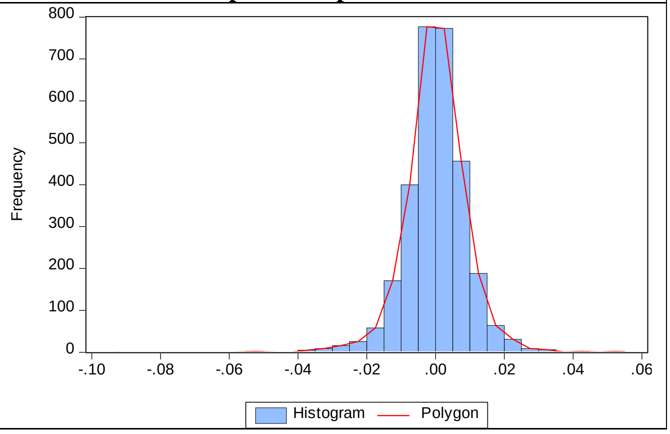
Table 1. Descriptive statistics of the Stoxx Europe 600 Food and Beverage Index

Statistics	Value	Graphical Representation
Mean	0.000153	
Median	0.000227	
Maximum	0.053182	
Minimum	-0.091960	
Standard Deviation	0.009087	
Skewness	-0.535217	
Kurtosis	9.954625	
Jarque-Bera	6189.079	
Probability Value of Jarque-Bera	0.000000	

Source: Author

Figure 1 presents the evolution of the Stoxx Europe Food and Beverage 600 price index and density of index returns from 2012 to 2024. I can observe the cyclical activity of food price index. Food price index increased dramatically between the end of 2011 and mid-2012. Prices then fell drastically in the final months of 2013, after reaching their highest level in 30 years in the first quarter of 2015. In the first few months of 2016, they reached a level slightly above that of 2015 and then rose in the first half of 2019 and over the course of 2019. They fell sharply between the end of 2019 and 2020. However, prices rose again in 2021 and peaked in the first quarter of 2022. The food index remains highly volatile to this day. The resurgence of food prices in 2019 and early 2022 has raised concerns about a potential recurrence of the 2006–2008 food crisis, along with growing fears of increasing food expences, food insecurity, and possible social unrest. The consensus in the literature is that the factors that caused an increase and greater volatility in food costs, ultimately resulting in the 2006-2008 food crisis –and subsequent fluctuation in food costs, occurred with more pronounced cycle activity in 2003. (Headey et al.(2010), Rezitis et al.(2013)).

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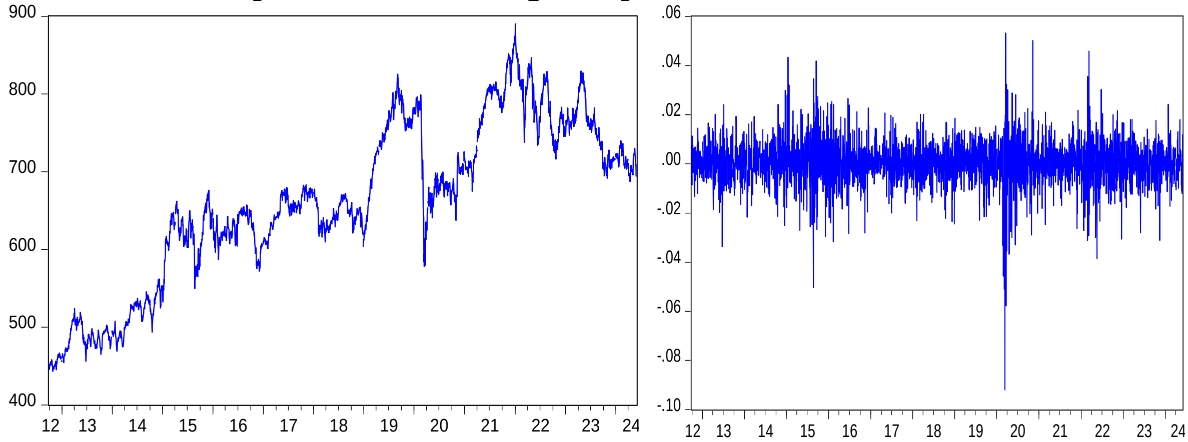
Graph 1. Evolution of Stoxx Europe Food and Beverage 600 price index and Evolution of Stoxx Europe Food and Beverage 600 price Return time series, 2012-2024



Source: Author

4.2 Empirical Findings

I apply the Fourier ADF stationarity technique proposed by Enders et al. (2012) to examine our index for potential structural breaks. First, I forecasted the Fourier ADF test statistic with time trend and intercept. I also incorporate up to three lags of the dependent parameter in the model and estimate each specification accordingly. In the test equation, I include up to three lags of the dependent variable and estimate each specification accordingly. The critical z-values corresponding to the 1%, 5%, and 10% significance levels are -2.333, -1.648, and -1.283, respectively. These results suggest that the data exhibit fluctuation cycles but do not show evidence of structural breaks. Significant fluctuations in the index indicate that there is uncertainty regarding the quantity of agricultural production and its prices. Revenues of main European food companies are affected by industry dynamics, economic conditions, demographics, and political regulations. If no structural breaks are detected in the data, Enders et al.(2012) recommend employing traditional stationarity tests. Following their guidance, I apply the conventional Augmented Dickey-Fuller test (Dickey & Fuller, 1981) alongside the Phillips-Perron stationarity test (Phillips & Perron, 1988). The results are shown in Table 3. The Stoxx Europe Food and Beverage 600 return series doesn't have unit root for the time span under consideration.

Table 2. Structural Break Test

		t-distribution critical value		
Z(t)	Test Statistic	1%	5%	10%
	-12.238	-2.333	-1.648	-1.283
p-value for Z(t) = 0.0000				

Source: Author

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Table 3. Unit Root Tests

	t-Statistic	Test critical values		
		1%	5%	10%
Augmented Dickey-Fuller test statistic	-54.28001* (0.0001)	-3.432341	-2.862305	-2.567222
Phillips-Perron test statistic	-54.28068* (0.0001)	-3.432341	-2.862305	-2.567222

- Significant at 5 percent significance level

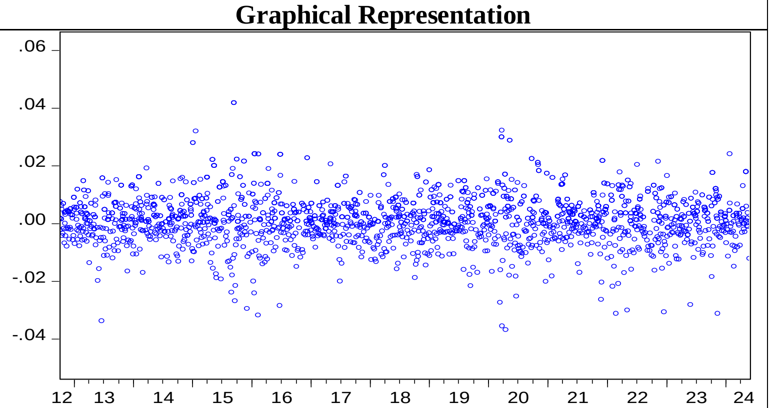
Source: Author

I use the ARMA (p, q) model of Ooms and Doornik (1999) to characterize the serial dependencies of return time series. Using Doornik's autoregressive and moving average algorithm, I ran a number of ARMA (p, q) models before determining which model fit the conditional values of the data the best and could predict them.

$$y_t = \varphi_0 + \sum_{i=1}^{R} \varphi_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{s} \varphi_i \varepsilon_{j-i} \quad (4)$$

The AR(1) MA(1) GARCH benchmark model effectively captures all dependencies in the return series of the sample, as the evaluated ARCH-standardized residual statistics show. To find out whether return series are volatile, I also use autoregressive conditional heteroscedasticity (ARCH) analysis. I first compute the residuals by regressing the index return series with the least squares (NLS) method. I then perform a regression of the squared residuals on both the lagged squared residuals and an intercept. The food industries of the European markets show an ARCH influence in the residuals, confirming that the variance component is not constant across the observations. Graphically, this means a variable dispersion of the points around the regression line. The result of the ARCH-LM test are shown in Table 4, and this outcome indicates that I can proceed with the GARCH family estimates for the conditional heteroscedasticity.

Table 4. ARCH-LM test result

Statistics	Value	Graphical Representation
F-statistic	8.41379 (0.0038)	
R-squared	8.34393 (0.0039)	

Source: Author

I proceed with the model of Engle and Ng (1993) to examine whether the return series demand an non-symmetric optimization process. The appropriate equation, which examines both magnitude and sign bias simultaneously, is as follows:

$$u_t^2 = \varphi_0 + \varphi_1 S_{t-1}^- + \varphi_2 S_{t-1}^- u_{t-1} + \varphi_3 S_{t-1}^+ u_{t-1} + \upsilon_t \quad (5)$$

I first estimate the GARCH (1,1) model and calculate its residuals. I also, create a new series in which I square these residuals. I then create two types of dummy variables. The first dummy variable takes the value 1 if the GARCH (1,1) residual series in the previous time period is less than zero and 0 otherwise. The second dummy variable is based on the values of the first one such as$1 - S_{t-1}^-$. The coefficient for the first dummy has a probability value well below 5%, indicating the presence of a sign bias. The coefficients for $S_{t-1}^-\widehat{u_{t-1}}$ and $S_{t-1}^+\widehat{u_{t-1}}$ are both significant with p-values of respectively. This is strong indicator of size effect. This test result serves as a good justification for estimating GARCH models that allow for asymmetric volatility. (Table 5).

Table 5. Engle and Ng test results

Sign bias	Coefficient	Probability
c	6.99E	0.0000
	-3.47E	0.0011
	-0.009328	0.0000

Size bias	Coefficient	Probability
c	5.19E	0.0000
	4.36E	0.0001
	0.002783	0.0081

Source: Author

The output of the GARCH model is provided in the Table 6. As a result, negative market shocks typically lead to a more persistent increase in conditional volatility than positive shocks of the same magnitude. Forecast accuracy shows that the model described in this paper is a good one and that it performs well in terms of forecasting. The combined coefficient of the ARCH and GARCH terms is 0.056025 + 0.886537 = 0.942562. Since this value is close to 1, it indicates that shocks to the conditional variance exhibit a high degree of persistence. These results are comparable to those of Rezitis et al. (2013), who highlight a high degree of persistence in the IMF monthly food price index for the period 1992–2012. This indicates that the European food

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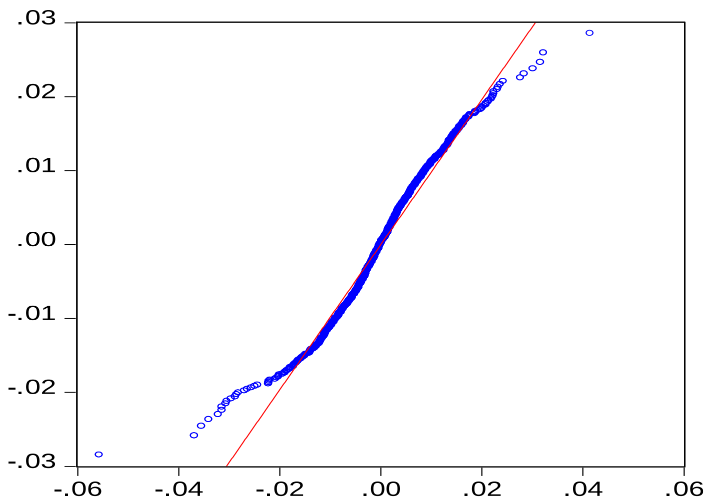
and beverage market is highly correlated leading to higher persistence in the market. The strong persistence of the European food market suggests that investors are not yet following a fixed investment philosophy and that their actions are susceptible to news about different innovations, whereby different types of innovations will cause different price reactions. The GARCH term is statistically significant, indicating that past prices affect the current price level. This result implies that a large excess return – either positive or negative - leads to high future forecasts of variance for a longer period of time. The Q–Q plot of the standardized EGARCH residuals was employed to assess the adequacy of the distributional assumption. We can see from Figure 2 that the residuals of EGARCH term doesn't deviate significantly and align closely with the 45-degree line in the central part of the distribution, indicating that the model can potentially capture the volatility dynamics.

Graph 2. Quantile to Quantile Plots of the EGARCH residuals



Source: Author

I identify the asymmetric effects of various market innovation types using the GJR-GARCH and EGARCH tools. Regardless of the values of the EGARCH equation's coefficients, the conditional variance in the EGARCH model is always guaranteed to be positive; even in the case of negative parameters, the conditional variance's logarithm will be positive. This is an advantage over the basic GARCH model. The output from the EGARCH estimates provided in Table 6 suggests that all parameters are statistically significant at a 5% significance level. The leverage coefficient, represented by γ, exhibits a significant negative value of -0.102121, suggesting asymmetric behavior. This suggests that, over the study period, negative shocks (or bad news) had a stronger impact on the next period's volatility than equally sized positive shocks (or good news). The stronger reaction of investors in the European food and beverage market to bad news compared to good news indicates that the volatility spillover mechanism in this market is asymmetric. This finding shows that investors overreact and dislike losses more than gains of similar magnitude. This condition can be seen as an overreaction anomaly in the European food and beverage market and may have an impact on index prices. Investors may take advantage of this market to realise abnormal trading returns. However, the overreaction anomaly is not evidence of European food and beverage market inefficiency, unless the trading strategy based on the abnormal profits is not consistent and disappear once attention of market participants' is drawn to it.

Considering the positive ARCH term of 0.135220, I can assume that there is a positive absolute value between the historical variance and the current variance. Additionally, Ican observe that the residuals of the EGARCH model deviate from normality on the negative side of the plane. In particular the function deviates most strongly between -0.04 and -0.02 values. The long and more pronounced negative cycle can be attributed to the interaction between the cyclical values of the separate commodity food price series that make up the aggregate commodity food price index during the averaging process. This results are compatible to those of Rezitis et al.(2013), who emphasize that a one-year cycle for livestock production, a two-year cycle for animal output, and a six-year cycle for perennial crops are frequently the outcomes of cyclical activity in agricultural food prices. The deviation is also observed on positive side between 0.2 and 0.4. Our finding is supported by Labys et al. (2000), who claim that the presence of cycles in a given area is consistent with the concept that a very significant (petroleum) price shock has permeated commodity markets.

However, the negative deviation from normality is larger than the positive deviation. This result graphically shows that food prices are more affected by negative uncertainty shocks than positive shocks and that negative market innovations cause longer negative cycles before approaching their trend value, shown with the red line. This implies that unforeseen, sudden, and disruptive market innovations have a deeper impact than upward shocks of the same size. This result is in line with the finding from Wen et al.(2021) who report similar findings for Chinese food market. Moreover, the GJR-GARCH model estimations are provided in the last column of the Table 6.

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Table 6: Estimation outcomes for models

Parameter	GARCH(1,1)		EGARCH		GJR-GARCH	
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Mean equation						
AR(1)	-0.855002	0.0000	-0.840578	0.0000	-0.849887	0.0000
MA(1)	0.871610	0.0000	0.858404	0.0000	0.865677	0.0000
Variance equation						
w	2.34E	0.0000	-0.419893	0.0000	2.48E	0.0000
α_1	0.087235	0.0000	0.135220	0.0000	0.002756	0.6144
β_1	0.883699	0.0000	0.966862	0.0000	0.901506	0.0000
΄Y	-		-0.102121	0.0000	0.126564	0.0000
ARCH-LM test	0.928575	0.3352	0.593596	0.4409	0.088704	0.7658

Source: Author

The statistical significance of the positive asymmetry term of the GJR-GARCH model γ= 0.126564 indicates that the impact of shocks are asymmetric, with negative shocks leading to an increase in volatility. This result supports the findings of the EGARCH specification. The models suggest on the asymmetric impact in the food and beverage industry of leading 600 European companies.

5. Conclusion

This study examines the volatility of the daily price index for food for the years between 2012(9) and 2024(6) using the GARCH model. In addition, I use EGARCH and GJR-GARCH tools to examine the variability of the STOXX Europe 600 food price index. These models are capable to capture non-linear trends and asymmetric processes in the return time series such as leverage effects, leptokurtosis and volatility clustering. As far as I am aware, the asymmetric dynamics of the daily index return volatility of the STOXX Europe 600 Commodity Food Price Index have not yet been studied in detail, especially with regard to the years of the 2019 pandemic crisis and its aftermath.

The results show that the STOXX Europe 600 Commodity Food Price Index deviates from normality and exhibits leptokurtic structures and negative skewness. In addition, the index shows a volatility clustering with an ARCH effect in the residuals, implying that the variance is not constant across the observations. The combined value of the ARCH and GARCH coefficients approaches unity, which means that the food return series have a long memory and the shocks experienced by the conditional variance are very persistent. This result suggests that there is a strong correlation between the European food and beverage market and higher market persistence. The remarkable resilience of the European food market suggests that investors lack a sound investment ethos, as evidenced by the fact that their actions are influenced by news about different innovations and that different innovations lead to different price reactions. The statistical significance of the GARCH term suggests that historical prices have an impact on current price levels. This result suggests that a significant excess return value, whether positive or negative, leads to high variance forecasts in the future for a longer period of time.

The findings from the EGARCH and GJR-GARCH models reveal the presence of a leverage effect and asymmetry in shock responses, indicating that negative shocks exert a stronger influence on volatility than positive shocks of the same magnitude. Possible drivers of the observed asymmetric volatility include the COVID-19 pandemic and the fact that nearly half of the index is concentrated in big firms. This impact make negative shocks to have a more pronounced impact on subsequent volatility compared to equally sized positive shocks. In addition, European food industry exhibits an asymmetric volatility spillover mechanism, also due to investors reacting more intensely to negative news than to positive news. This is evidence of investors overreaction and can affect the index prices. Investors can take advantage of this market to generate abnormal trading returns. However, the overreaction anomaly is not evidence of European food and beverage market inefficiency, unless the trading strategy based on the abnormal rewards is not consistent and disappears once investors’ attention is drawn to it.

I observe, the long and more pronounced negative cycle in the EGARCH model. The longer and more pronounced negative cycle could be explained by the way the averaging process interacts with the cyclical values of the individual food price series that make up the aggregate food price index.

This study visually demonstrates that negative uncertainty shocks exert a greater influence on food prices than positive shocks, and that negative market innovations lead to longer negative cycles before the food price approaches its trend value. Given that excessive food price volatility often has a negative impact on the domestic economy, policymakers should take note of this empirical evidence. Policy makers, especially in emerging economies, should look for ways to support the domestic food economy and strengthen the food industry through coordination efforts between domestic and international economic policies to diminish the negative influence of variability on economic linkages. The empirical observations of this study have important implications for trade decisions and portfolio management. Investors should be aware of the potentially extreme volatility and asymmetric dynamics in the food stock markets and construct their portfolios accordingly. The empirical results of this study have implications for households, domestic and international companies.

There are some limitations of this study. The more apparent limitations is that, the study period is based on data availability, which may overlook earlier structural shifts or historical volatility patterns, potentially affecting long-term comparability. External macroeconomic factors (e.g., global commodity prices, exchange rates, geopolitical risks, and climate-related shocks) are not explicitly incorporated, even though they may influence volatility patterns. Future studies can extend the analysis by incorporating alternative volatility models such as APARCH, TGARCH, NGARCH, or stochastic volatility models to test robustness and improve explanatory power. In addition, they can integrate exogenous explanatory variables such as global food commodity prices, energy costs, inflation, and exchange rates to capture broader drivers of volatility.

References

Adeosun, O. A., Olayeni, R. O., Tabash, M. I., & Anagreh, S. (2023). *Revisiting the oil and food prices dynamics: A time varying approach*. Journal of Business Cycle Research, 19(3), 275-309.

Adjemian, M. K., Arita, S., Meyer, S., & Salin, D. (2024). *Factors affecting recent food price inflation in the United States*. Applied Economic Perspectives and Policy, 46(2), 648-676.

Baffes, J. (2007). *Oil spills on other commodities*. Resources Policy, 32(3), 126-134.

Dickey, D. A., & Fuller, W. A. (1981). *Likelihood ratio statistics for autoregressive time series with a unit root*. Econometrica, 49, 1057–1072. https://doi.org/10.2307/1912517.

Cardoso, F., Peixoto, M., & Esteves, L. (2021). *Commodity price volatility and the COVID-19 pandemic: Evidence from food markets*. Journal of Commodity Markets, *22*(3), 100–117.

Doornik, J.A., & Ooms, M. (1999). *A Package for Estimating, Forecasting and Simulating Arfima Models*: Arfima package 1.0 for Ox.

Enders, W., & Lee, J. (2012). *The flexible Fourier form and Dickey–Fuller type unit root tests*. Economics Letters, 117(1), 196–199. https://doi.org/10.1016/j.econlet.2012.04.081.

Engle, R. F. (1982). *Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation*. Econometrica, 50, 987–1007. https:// doi.org/10.2307/1912773.

Engle, R. F., & Ng, V. K. (1993). *Measuring and testing the impact of news on volatility*. The Journal of Finance, 48, 1749–1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x.

Gönderim tarihi: 28.04.2025 Kabul tarihi: 01.06.2026
DOI: 10.14514/beykozad.1667418

Erten, B., & Ocampo, J. (2021). *The future of commodity prices and the pandemic-driven global recession: Evidence from 150 years of data*. World Development, 137, 105164.

Filip, O., Janda, K., Kristoufek, L., & Zilberman, D. (2019). *Food versus fuel: An updated and expanded evidence*. Energy Economics, 82, 152-166.

Gilbert, C. L. (2010). *How to understand high food prices*. Journal of Agricultural Economics, 61(2), 398-425.

Ginn, W. (2023). *World output and commodity price cycles*. International Economic Journal, 37(4), 530-554.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). *On the relation between the expected value and the volatility of the nominal excess return on stocks*. The Journal of Finance, 48(5), 1779–1801.

Headey, D., & Fan, S. (2010). *Reflections on the global food crisis: How did it happen? How has it hurt? And how can we prevent the next one?* (Vol. 165). Intl Food Policy Res Inst.

Jebabli, I., Arouri, M., & Teulon, F. (2014). *On the effects of world stock market and oil price shocks on food prices: An empirical investigation based on TVP-VAR models with stochastic volatility*. Energy Economics, 45, 66-98.

Koopman, S. J., Harvey, A. C., Doornik, J. A., & Shephard, N. (2000). STAMP 6.0: *Structural time series analyser, modeller and predicto*r. London: Timberlake Consultants.

Labys, W. C., Kouassi, E., & Terraza, M. (2000). *Short-term cycles in primary commodity prices. The Developing Economies*, 38(3), 330-342.

Mawejje, J. (2016). *Food prices, energy and climate shocks in Uganda. Agricultural and Food* Economics, 4(1), 4.

Mitchell, D. (2008). *A Note on rising food prices*, Policy Research Working Paper #4682 (Washington,DC: World Bank, Development Prospects Group).

Nelson, D. B. (1991). *Conditional heteroskedasticity in asset returns: A new approach*. Econometrica, 59(2).

Phillips, P. C., & Perron, P. (1988). *Testing for a unit root in time series regression*. Biometrika, 75(2), 335–346. https://doi.org/10.1093/biomet/75.2.335.

Rosegrant, M. W., Zhu, T., Msangi, S., & Sulser, T. (2008). *Global scenarios for biofuels: impacts and implications.* Review of agricultural economics, 30(3), 495-505.

Rezitis, A. N., & Sassi, M. (2013). *Commodity food prices: review and empirics*. Economics Research International, 2013(1), 694507.

Ridler, D., & Yandle, C. A. (1972). *A Simplified method for analyzing the effects of exchange rate changes on exports of a primary commodity*. Staff Papers-International Monetary Fund, 559-578.

Sharma, S., & Kumar, R. (2006). *Asymmetric volatility in agricultural commodity markets: Evidence from India*. Agricultural Economics Research Review, *19*(2), 25–40.

Sun, Y., Gao, P., Raza, S. A., Shah, N., & Sharif, A. (2023). *The asymmetric effects of oil price shocks on the world food prices: Fresh evidence from quantile-on-quantile regression approach.* Energy, 270, 126812.

Tetteh, J., & Amoah, B. (2021). *COVID-19 and food price volatility in sub-Saharan Africa*. Food Policy, 104, 102129.

Wen, J., Khalid, S., Mahmood, H., & Zakaria, M. (2021). *Symmetric and asymmetric impact of economic policy uncertainty on food prices in China: A new evidence*. Resources Policy, 74, 102247.

Yoon, S. M. (2022). *On the interdependence between biofuel, fossil fuel and agricultural food prices: Evidence from quantile tests*. Renewable Energy, 199, 536-545.

Umar, Z., Gubareva, M., Naeem, M., & Akhter, A. (2021). *Return and volatility transmission between oil price shocks and agricultural commodities*. PLoS One, 16(2), e0246886.

Zhang, D., & Broadstock, D. C. (2020). *Global financial crisis and rising connectedness in the international commodity markets*. International Review of Financial Analysis, 68, 101239.