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DOES FEAR (VIX INDEX) INCITE VOLATILITY IN FOOD PRICES?

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Abstract

Globally, the volatility trend in food prices has continued to increase. Different data give the impression that this volatility may be caused by the international finance markets' propagation effect. For this reason, the study focused on the VIX (fear) index that is used to measure the movement in Standard & Poor's 500 index. The main objective of the study is to analyze the degree of volatility between the VIX index and the wheat market. The research is comprised of monthly data obtained from year 2000 to 2015. The study employs the BEKK GARCH method. The findings show that the variance shocks in the fear index damage food prices. The results may be useful to policy makers in researching the causes of changes in the prices of food commodity and taking necessary measures.
Keywords: *Food prices, Fear (VIX) index, BEKK GARCH model*
JEL Code: *Q14, Q18, E3*

1. Introduction

The cost of food prices is an important risk factor especially as regarding inflation. Therefore, the food price volatility may affect the nations' general welfare level. In recent times, the volatility, undesired by the policy makers as well as the actors in the market, increased its impact on food prices. According to the International Monetary Fund (IMF),the food price index datashows that prices increased more than twofold within a five-year period, between 2003 and 2008. However, this increment did not last long and the price index regressed at the end of the year 2008. The index, having increased until 2011, continued its volatile trend by a decrease in 2012 and another increase in 2013. These volatile moves, also observed in other commodities,such as agriculture and the remainderof market indexes, rather than price indexes, might be an indicator of inter-market propagation. The number of future and optional contracts increment abovefivefold in the 2002-2008 period, and the commodity values increment of more than twenty-fold,thereby reaching 13 trillion,as confirmed by USD (UNCTAD, 2009). Krugman (2008) stated that, even though commodity prices are defined by economic principles, in shorter terms, expectations may drive prices. According to him, global economic developments, news or sudden short-term expectation of a price increase may affect production and stocks. Hamilton (2008, 2009) supports this argument by suggesting the non-movement of the offer curve as a reason for this situation. Especially in agricultural products with long production intervals, the offer may not respond to a probable volatility in a short term. Therefore, volatility may be stronger in products with lower offer elasticity but this situation may be overcome by economic principles. Thus, market expectations is relevant. Indexes are among the most important indicators of market expectations. The most commonly used among them are the “Standard & Poor’s Goldman Sachs Commodity Index” and the “Dow Jones–Union Bank of Switzerland Commodity Index.” The study focused on the VIX (fear) index that was used to measure the movement in Standard & Poor’s 500 index. The primary objective of the research is to define the probable effects of VIX index volatility on global food prices. This study may help policy makers in understanding the causes of volatility in food prices and assessing the effectiveness of policies employed.

2. Previous Studies

The volatility in food prices has been discussed by several scholars of different views.During this period, different markets acting in unison with the food prices, incite scholars to research on the effect of non-market-based structures affecting prices. Among different observations,financing of agriculture markets stands out as one of the most important issues. Accordingly, effects of speculators’ change of positions on spot markets were studied (Bohl and Stephan 2013). However; while some studies find a positive relationship between moves and spot markets (Yang *et al.,* 2005), others could not reach a conclusion on such findings (Irwin and Sanders, 2012; Miffre and Brooks, 2013;Demirer *et al.*, 2015). Meanwhile, in some studies, negative relationship is observed (Aulerich *et al.,* 2013a; Power and Turvey, 2011). According to Gilbert (2010), speculative moves occur generally by uninformed speculators following trend speculations. These were counterbalanced by informed speculators that can read economic principles properly. Thismight all happen in a short term. On the other hand, data issues caused by the accumulation of positions in different terms complicate the definition of these moves in relation to the market. Furthermore, the difficulties in categorizing position takers in the derivative markets as commercial and non-commercial, further aggravates this uncertainty. Several researchers have employed different methods to overcome this issue. For instance, Bryant *et al.*, (2006), used long and short term contracts speculatively,this was based on the definition of commercial and non-commercial traders by the Commodity Futures Trading Commission (CFTC). While this approach could partially distinguish commercial and non-commercial trading, the data collection method varies per researcher. In this regard, scholars such as Aulerich *et al.*, (2013b); Bohl *et al.*, (2013) treated variables per short positions, while Irwin and Sanders, (2011) treated variables per long positions, and Sanders and Irwin, (2011) per net positions. Researchers such as Cinar *et al.*, (2015) and Andreasson *et al.*, (2016) conducted their analyses per Working’s T-index that calculates both position types together. It may also be noted that, the findings reached in these researches are not in agreement. The main reason for differences is the observational difficulty in speculator moves and the differences in data selection processes. As a matter of fact, investors may take positions based on a commodity index of a wide selection commodity contracts, varying from agricultural products to energy products. Therefore, investors may take positions in a herd behavior, rather than following the conditions of all commodities one by one. At this point, the expectations arising from global financial markets become important (Burch and Lawrence, 2009). Therefore, expectations, rather than positions, may be emphasized in researching the effects of financial markets. In line with this argument, Hartelius *et al.*, (2008) claimed that the VIX (fear) index marking volatility in the SP-500 Index is a strong indicator for defining both the investor behavior and the global market conditions. Similarly, in the global financial stability report by the IMF (2004), it is stated that the fear (VIX) index is an important variable reflecting investors’ attitude toward risk. In the literature review, it may be said that the studies conducted using the fear index focusedmainly on oil (Sari *et al.*, 2011), gold (Jubinski and Lipton, 2013) and currency (Liu *et al.*, 2013) markets. Studies on the relationship between food prices and the fear index are rather scarce. In this study, the relationship between food price volatility and the VIX index is examined. In the following part of the research, the data and the model will be introduced and the subsequent part will feature findings. The final part is comprised of the conclusion and suggestions.

3. Material And Method

In the study, the monthly data between January 2000 and December 2015 were used. The principal reason for choosing such dates is that the volatility in food prices started to increase after this period. The variables used in the research are given in Figure 1. The fear (VIX) index data is collected from the Chicago Board Options Exchange website, the Food Prices Index (FPI) data is collected from the official website of Food and Agriculture Organization of the United Nations (FAO). The VIX index is dependent on the American stock prices. When the volatility in this stock market increases, the index goes up, and it goes down when the price volatility decreases. The VIX index has been on an increasing trendsince 2008, while it decreased in 2009. In 2011, it increased again to the level of 40 points. The index having decreased to the 14-18 band in 2013, surpassed the 20 band in mid-2015 (Figure 1). It may be said that the index reached its peak in the 2008 mortgage (subprime) crisis and the 2010 European debt crisis. The FAO food index is comprised of five main commodity groups and a total of 73 food item prices, weighed per volume in trading. The peak of this index was reached in 2008,having 201 points. However, in December 2015, the general food prices were 24% lower compared to the year 2008. When the food prices are examined per year in monthly intervals, it has been found that the volatility is much more visible (Figure 1).

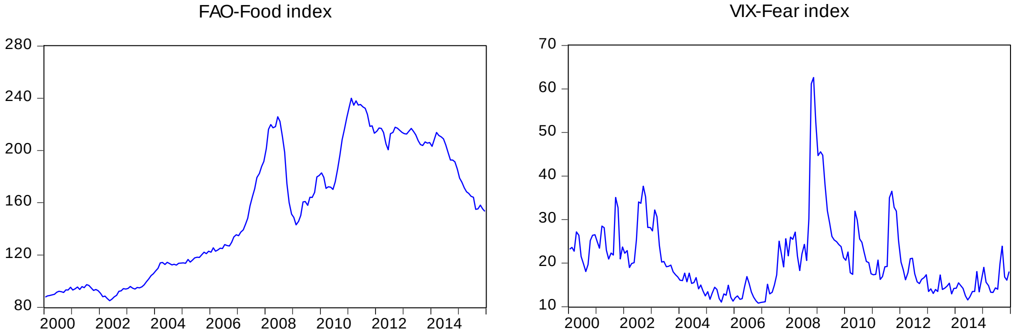

Figure 1. Movement of Variables

Table 1. Descriptive statistics

	FAO-Food Price Index (FPI)	VIX-Fear Index
Mean	153.8009	20.64550
Median	155.1150	18.36192
Maximum	240.0900	62.63947
Minimum	85.08000	10.81762
Std. Dev.	49.23155	8.545734
Skewness	0.110927	1.963823
Kurtosis	1.530907	8.593438
Jarque-Bera	17.65964***	373.7036***
Observations	192	192

Notes: *** denote statistical significance at 1% level of significance

In Table 1, definitive statistics related to variable used in the study are given. For the data, the results of Jarque-Bera test statistics refute normality condition at 1% significance level. In Skewness vs Kurtosis statistics, the variables lean to the right and the fear index has a fat tail. Standard deviation data show that price index volatility is significantly stronger than the fear index. Complementary statistics show that GARCH-type models may be adopted to these two datasets. However, for this method to be adopted, broader analysis is required.The ARCH (autoregressive conditionally heteroscedasticity) process is proposed by Engle (1982), however, since too many parameters are needed to explain volatility, the issue of negativity in lagged values occurs.

For this reason, Bollerslev (1986), by expanding the ARCH model with more past information and a more flexible lag structure, proposed a generalized ARCH (GARCH) model. In GARCH models, conditional heteroscedasticity in period t, does not depend solely on past values of error terms, but also on conditional heteroscedasticity in the past. The principal BEKK (Baba-Engle-Kraft-Kroner) GARCH model equation used in this study is as shown below (Engle ve Kroner, 1995).

$$FPI= c+\varepsilon_t \qquad (1)$$

$$\varepsilon_t \sim N[0, (\alpha_0 + \alpha_1 + \varepsilon^2_{t-1})] \qquad (2)$$

$$h_t = \alpha_0 +\alpha_1\varepsilon^2_{t-1} +\beta_1 h_{t-1}+ \delta VIX_{t-p}+ \varepsilon_t \qquad (3)$$

Equality 1 represents the average equation. Equality 2 represents normal distribution condition of variance under zero average. Equality 3 is time conditional variance model (h_t). In this model, lagged squared errors (ε^2_{t-1}), time conditional variance term (h_{t-1}), and VIX index as variance regression are used. The parameters to be estimated are α_1, β_1, α_0 and δ. The constraints for estimation parameters should be as shown: $\alpha_1+\beta_1<1$, $\alpha_0>0$. If the sum of $\alpha_1$and $\beta_1$coefficients is between 0.9 and 1, it may be said that time-varying volatility is high.

4. Research Findings

For the GARCH model used in the research, firstly, the series should be stationary. Augmented Dickey-Fuller (ADF) unit root test results show that variables' level values are not stationary (Table 2). For variables first-order difference of which was taken, null hypothesis is refuted in 1% level of significance. Accordingly, it may be stated that variables do not have unit root and they are stationary.

Table 2. Augmented Dickey Fuller (ADF) Unit Root Test Results

Variable	Level	ADF Constant		ADF Trend-Intercept	
		t-Statistic	Prob.	t-Statistic	Prob.
VIX	I(0)	-3.2376	0.0194**	-3.3042	0.0687
FPI	I(0)	-1.5703	0.4963	-2.5025	0.3267
VIX	I(1)	-11.597	0.0000***	-11.566	0.0000***
FPI	I(1)	-10.062	0.0000***	-10.043	0.0000***

Notes: ** and *** denote statistical significance at 5% and 1% level of significance respectively

In Table 3, the Ljung-Box Q statistics of lagged ARMA model coefficients of these two market is shown. The test results suggest strong evidence on autocorrelation for the two markets. Meanwhile, Jarque-Bera test statistics (24.45406; p<0.000005) show that the series do not comply with normal distribution. Moreover, Brusch-Pagan-Godfrey testresults clearly stated that there is a varying variance problem between these variables. (F statistics 7.358025; p=0.0073).

Table 3. Ljung-Box Q statistics

Lag	AC	PAC	Q-Stat.	Prob.	Lag	AC	PAC	Q-Stat.	Prob.
1	0.490	0.490	46.600	0.000	13	0.156	-0.024	179.37	0.000
2	0.438	0.261	84.082	0.000	14	0.136	0.001	183.21	0.000
3	0.210	-0.108	92.756	0.000	15	0.216	0.129	193.02	0.000
4	0.199	0.055	100.58	0.000	16	0.138	-0.111	197.04	0.000
5	0.132	0.034	104.05	0.000	17	0.124	0.001	200.32	0.000
6	0.212	0.139	113.00	0.000	18	0.037	-0.114	200.61	0.000
7	0.244	0.130	124.93	0.000	19	0.072	0.041	201.73	0.000
8	0.212	-0.024	134.03	0.000	20	-0.000	-0.019	201.73	0.000
9	0.319	0.203	154.69	0.000	21	0.197	0.180	210.11	0.000
10	0.189	-0.073	161.99	0.000	22	0.136	-0.015	214.12	0.000
11	0.174	-0.039	168.22	0.000	23	0.156	-0.038	219.49	0.000
12	0.173	0.128	174.35	0.000	24	0.113	-0.019	222.33	0.000

Additionally, it is possible to observe the existence of the ARCH (F statistics 59.61487; p=0.0000) effect in the series. Finally, in Figure 2, the volatility clusters of variables' errors are presented. Between 2007 and 2012, high fluctuations are observed. All performance indicators show that the GARCH method should be used definitely in defining volatility between two variables.

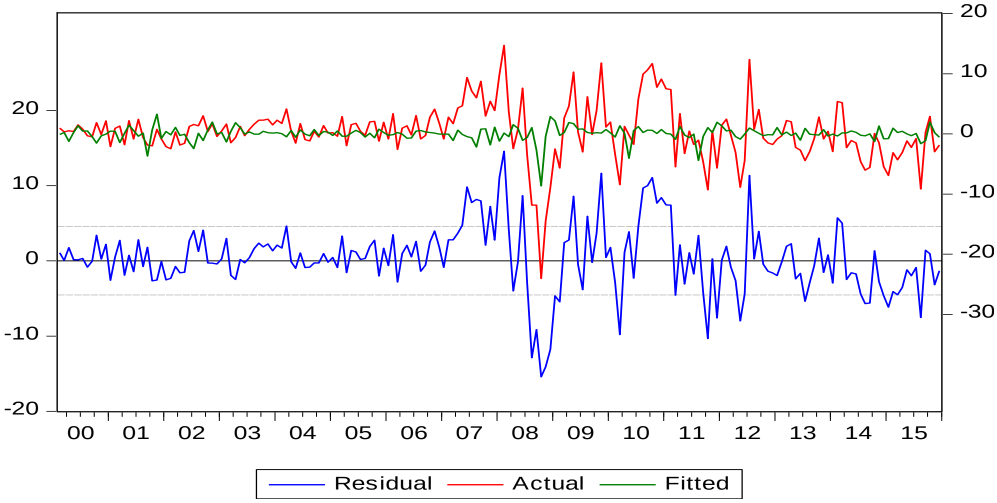

Figure 2. Volatility Clusters of ARMA Model Errors

The results of the model used in the research are given in Table 4. The Akaike value for the GARCH(1,1) model established for the research is 5.391 and the Schwarz value is 5.494;

while the Akaike value for GARCH(2,1) modelis 5.236 and the Schwarz value is 5.355. As a decrease in the Akaike and Schwarz data criteria is observed in GARCH(2,1) and above models, the GARCH(1,1) model is preferred. Meanwhile, in the selection of model distribution criterion, a generalized error distribution (GED) was used. This is principally caused by the data not complying with normal distribution criteria and the performance criteria of variables having more successful results compared to other distributions. In Table 4,the variance equation results for GARCH(1,1) model are given. In table 4, the mean in heteroscedasticity is 3.29, volatility shock is 0.57, and the effect of the previous period volatility to the following period is 0.37 units.It is observed that estimation parameters complied with the $\alpha_1+\beta_1<1$ and $\alpha_0>0$constraints.

Table 4. Coefficient Estimates of Fitted GARCH Model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.420923	0.247330	1.701864	0.0888
Variance Equation				
α_0	3.297418	1.454594	2.266900	0.0234**
α_1	0.571225	0.049518	11.53559	0.0000***
β_1	0.376353	0.095376	3.946006	0.0001***
δ	0.924106	0.209284	4.415566	0.0000***
GED parameter	1.634244	0.330664	4.942306	0.0000***

Notes: ** and *** denote statistical significance at 5% and 1% level of significance respectively

When $\alpha_1+\beta_1$ parameters are examined, it may be speculated that the volatility continuity is high and the panic experienced in the US financial markets might give long term (0.94) damages over FAO general food prices. It was observed that the parameters used in the research, including the generalized error distribution parameter, are statistically significant ($p<0.05$).

These findings support the previous studies (Gözgör and Kablamacı, 2014). However, it should be verified whether there has been a change or not in the performance criteria applied before, in order to define this model’s usability. If there have not been any positive developments in these performance criteria, it is not suitable to interpret model results. Accordingly, the variables that do not comply with normal distribution in the ARMA model should enter the normal distribution line in the GARCH model.

In Figure 3, the defining statistics of the GARCH model and the distribution situation is given as Jarque-Bera test statistics, the model residues comply with normal distribution conditions under the significance level of 5%.

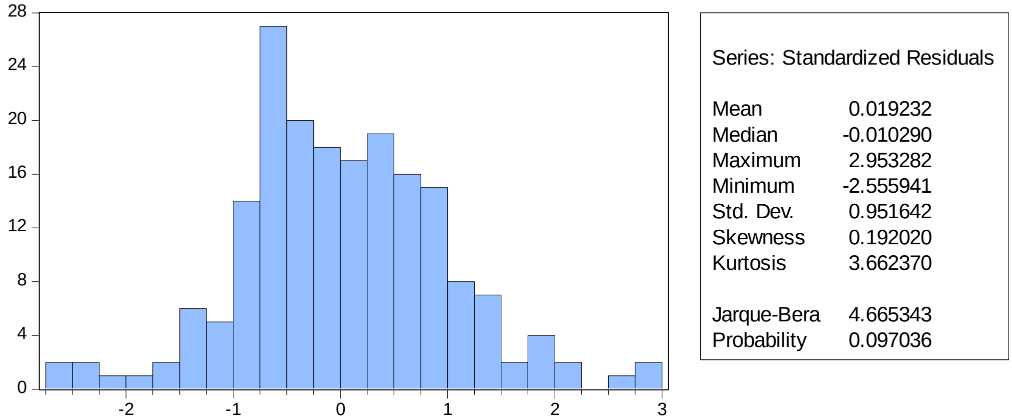

Figure 3. Descriptive Statistics and Normality Test of the Residuals of the Fitted Model

In Table 5, Ljung-Box Q statistics are presented. This test producing strong evidence on autocorrelation in the ARMA models, shows that the autocorrelation issue is resolved in the GARCH models.

Table 5. Ljung-Box Q statistics

Lag	AC	PAC	Q-Stat.	Prob.	Lag	AC	PAC	Q-Stat.	Prob.
1	-0.001	-0.001	0.0001	0.992	13	0.022	-0.016	13.737	0.393
2	0.017	0.017	0.0591	0.971	14	0.112	0.077	16.354	0.292
3	-0.066	-0.066	0.9099	0.823	15	0.165	0.145	22.056	0.106
4	0.053	0.053	1.4566	0.834	16	0.050	-0.001	22.576	0.126
5	0.000	0.002	1.4566	0.918	17	0.002	-0.002	22.576	0.164
6	0.096	0.090	3.2769	0.773	18	-0.020	-0.037	22.665	0.204
7	0.157	0.166	8.2054	0.315	19	0.065	0.028	23.569	0.213
8	0.051	0.049	8.7260	0.366	20	-0.078	-0.104	24.885	0.206
9	0.146	0.163	13.053	0.160	21	0.098	0.024	26.969	0.172
10	0.041	0.063	13.393	0.203	22	0.087	0.040	28.604	0.157
11	-0.007	-0.014	13.402	0.268	23	0.113	0.056	31.393	0.113
12	0.034	0.047	13.633	0.325	24	-0.017	-0.043	31.454	0.141

Additionally, in the ARMA model, there is the existence of an ARCH effect between two market residues. In the GARCH model,the ARCH effect disappears (F statistics 0.0000988; p=0.9921). It can be said that variances issue does not exist over errors. The conditional variance change of the GARCH model, defined as the best model, is given (Figure 4) in order to assess its volatility. Using conditionally changing variance models facilitates estimating volatility over time. Per this model, it may be said that the food price volatility increased in crisis periods and this volatility trend decreased after the year 2007. Besides, the highest volatility between the food price index and the fear index is observed in 2008-2009.Generally, it may be stated that the propagation effect of the fear experienced by the US financial markets became permanent after the crisis period. This data supports the argument that the relationship between the food markets and the financial markets intensified after the food crisis (Tadasse *et al.*, 2016).

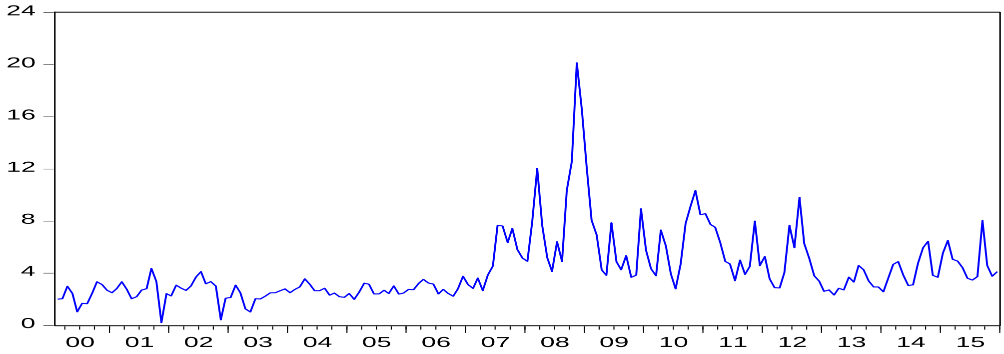

Figure 4. The Conditional Standart Deviation Change of the GARCH Model

5. Conclusion

In this study, the effects of the VIX index volatility over global food prices are defined using the GARCH model. According to the findings, two important results are stated. Firstly, the financial developments in developed countries, such as the United States is influent over food prices. Because of globalization, the global negative developments may affect different markets on a short-term and increase the vulnerability of markets. More importantly, the increasing numbers of import in developing nations made the domestic food prices to be integrated to the international prices. This situation may create consequences that affect the general welfare level in countries that devote an important part of their budget to food expenses. In this regard, it may be suggested that staple food needs may be met especially through domestic supply, which is less affected by the food price volatility. The upcoming studies on this subject should be focused on the dynamic propagation of external shocks by economic and financial variables causing financial disorder (that is, inflation, interest rates, and currency rates) over food prices. Secondly, it has been found that the volatility effect of food prices increased after the year 2007, compared to the previous period.Based on this information, the food prices had a breakpoint at that period and became more dependent on the present financial indicators. Therefore, the agriculture market may face a pricing factor exceeding the supply and demand equilibrium. This suggests the need for observing financial markets. The participation of financial institutions to the commodity markets should be followed closely,especially, the active commodity trading by big investment banks should be kept under control. Strengthening financial regulations on commodity markets may reduce their effect over food prices. Accordingly, developing nations may apply pressure for new financial regulations through international institutions. In new researches, the relationship between markets over positive and negative shocks should be given more attention.

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