Forecasting agricultural price volatility of some export crops in Egypt using ARIMA/GARCH model

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Abstract

Purpose – This study focuses on forecasting the price of the most important export crops of vegetables and fruits in Egypt from 2016 to 2030.

Design/methodology/approach – The study applied generalized autoregressive conditional heteroskedasticity (GARCH) model and autoregressive integrated moving average (ARIMA) model.

Findings – The results show that ARIMA (1,1,1), ARIMA (2.1,2), ARIMA (1,1,0), ARIMA (1,1,2), ARIMA (0,1,0) and ARIMA (1,1,1) are the most appropriate fitted models to evaluate the volatility of price of green beans, tomatoes, onions, oranges, grapes and strawberries, respectively. The results also revealed the presence of ARCH effect only in the case of Potatoes, hence it is suggested that the GARCH approach be used instead. The GARCH (1,1) is found to be a better model in forecasting price of potatoes.

Originality/value – The study of food price volatility in developing countries is essential, since a significant share of household budgets is spent on food in these economies, so forecasting agricultural prices is a substantial requirement for drawing up many economic plans in the fields of agricultural production, consumption, marketing and trade.

Keywords Forecasting, Agricultural price, Volatility, Export crops, ARIMA, GARCH model

Paper type Research paper

1. Introduction

Monitoring the volatility commodity prices can play a key role in a country's overall economic performance. Therefore, the commodity price forecast helps decision-makers to develop appropriate economic policies and strategies that are compatible with the future changes (Bhardwaj *et al.*, 2014).

Commodity prices, especially the prices of agricultural commodities, are subject to high degrees of volatility; therefore, the predictable price decreases the negative impact of uncertainty, in other words, decrease producer aversion to risk (Sedghy *et al.*, 2016).

In general, fluctuations in prices of agricultural commodity occur primarily from shocks of the supply side. These disturbances, combined with the short-term demand and supply elasticity coefficients, lead to sharp instability of the price (Sendhil *et al.*, 2014; Piot-Lepetit and M'Barek, 2011), which lead both farmers and consumers to uncertainty and risk and so volatility of commodity prices has been studied (Apergis and Rezitis,2011; Ahmed and Serra, 2015).

More critical is the analysis of food price fluctuations in developing countries, since a significant share of household income is spent on food in these economies, so uncertainty

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about food prices has a direct effect on welfare. Instability of food price is particularly affecting low income people, small agricultural producers who depend on crop sales for a significant portion of their income (Ceballos *et al.*, 2017; Sedghy *et al.*, 2016).

The research problem is identified the most suitable models to evaluate the volatility of the most important Egyptian export crops of vegetables and fruits, so this study aims to forecast agricultural prices for green beans, potatoes, tomatoes, onions, oranges, grapes and strawberries using the ARIMA or GARCH approach.

2. Literature review

Various empirical studies have analyzed measuring and forecasting agricultural price volatility of different products using ARIMA-GARCH models. Felis and Garrido (2015) studied price volatility in Spain of fresh fruits and vegetables, using multivariate GARCH model. In the Spanish tomato marketing chain, Sidhoum and Serra (2016) applied the MGARCH model to test spillovers of uncertainty.

Lama *et al.* (2015) analyzed the price volatility in agricultural market, especially for three main commodities: the international price of edible oils, the international price of cotton and the domestic price of edible oils depending on ARIMA model, GARCH model and EGARCH model. Ramirez and Fadiga (2003) and Sanjuan-Lopez and Dawson (2017) studied the volatility price of soybeans and wheat in the United States futures markets through the GARCH model. Sekhar *et al.* (2017) applied GARCH and EGARCH to examine volatility in agricultural price in India, while Guerrero *et al.* (2017) used these models to analyze agricultural price volatility in both Mexican agricultural market and international agricultural market.

For the period from January 1990 to February 2014, Ojogho and Egware (2015) studied the price volatility of sugar, meat, grain, dairy and gross food in the Nigeria. Also Kamu *et al.* (2010), Onour and Sergi (2011), Sukati (2013), Bhardwaj *et al.* (2014), Sendhil *et al.* (2014), Sedghy *et al.* (2016), Solanki and Sharma (2016) and Lama *et al.* (2016) applied ARIMA-GARCH model to analyze and forecast price volatility of some selected agricultural products.

Yang *et al.* (2001) analyzed the impact of the liberalization of agricultural sector on the volatility of commodity price through GARCH application; results of the study showed that agricultural liberalization policy increases the market volatility for some grain crops. Siami and Hudson (2017) used an AR-EGARCH model to analyze the interdependent relationship between futures prices of crude oil, international prices of agricultural products and exchange rate.

Other empirical studies focused on measuring and forecasting price volatility of agricultural products using other econometric models. Corrêa *et al.* (2016) used a new causal forecasting approach, called (WARIMAX-GARCH) method; Benavides (2009) used an option implied approaches, GARCH model, a multivariate ARCH and composite approaches to predict futures prices of some cereal. Li *et al.* (2017) proved that the two-state normal mixture (NM)-GARCH approach is more accurate than the GARCH model in modeling agricultural price volatility. Jin and Frechette (2004) confirmed that the results of fractional integration (FI) GARCH model perform significantly better than traditional normal GARCH.

Anggraeni *et al.* (2017) applied Vector Autoregressive model and an ARIMAX model to predict the price volatility of rice in Indonesia. Xiong *et al.* (2015) predict some of agricultural commodity prices in China with VECM–MSVR model, which is a combination of the linear and nonlinear methods. On the other hand Zou *et al.* (2007) ensured that the artificial neural network (ANN) model is the best model for forecasting the future price of Chinese cereal. While Haofei *et al.* (2007) used a multi-stage optimization approach (MSOA) to predict cereal price in China. Xiong *et al.* (2018) applied a hybrid STL and ELM methodology to predict the Chinese vegetable price and to evaluate the volatility of it in the short and long run.

The main contribution of this paper is that the published works regarding price volatility of agricultural prices in Egypt are so little. El-Rasoul and Tolba (2018), analyzed the price volatility in the Egyptian food markets to find the major macroeconomic factors that influence it during the period 1995–2015 through the exponential function model. The results revealed that there is some link between the seasonality of retail prices and the wholesale prices of the commodities studied.

Abdelfattah *et al.* (2015) studied price volatility in the Egyptian markets of surge crops from 1998 to 2013 using ARIMA model. Abdel-Radi and Ahmed (2018) aims to study the price volatility of the Egyptian wheat market during the period (2008–2013) depending on BEKK-GARCH model, and the study also examined how the shocks in the international wheat market influence the Egyptian domestic market.

3. Materials and methods

3.1 The data

The study employs observations for producer prices of the most important Egyptian export crops of vegetables and fruits, including green beans, potatoes, tomatoes, onions, oranges, grapes and strawberries. All the variables are in logarithmic form. The study period 1967: 2015 except strawberries the available data only from 1991 to 2015. The main source of data was Food and Agriculture Organization (FAO) database.

3.2 Methodology

3.2.1 ARIMA model. The ARIMA is among the most common models for the study of time series forecasting. In this model, the future value of a variable is supposed to be a linear combination of past values and past errors (Guerard, 2013; Khashei and Hajirahimi, 2017; Badmus and Ariyo, 2011).

The ARIMA methodology is performed in four stages or steps, including: identification, estimation, diagnostic checking and forecasting (Kamu *et al.*, 2010).

3.2.2 ARCH–GARCH model. The autoregressive conditional heteroskedasticity (ARCH) model and the generalized ARCH (GARCH) model specify explicitly how conditional variances evolve over time (Han *et al.*, 1990; Wang *et al.*, 2002; Luger, 2012).

ARCH models permit the shocks in more recent periods to have a positive effect on current volatility; on other hand the GARCH models assume that current volatility is influenced not only by past shocks, but also by past volatilities (O'Connor and Keane, 2011; Engle, 2001, 2002; Bauwens *et al.*, 2006).

4. Results and discussions

4.1 ARIMA model

4.1.1 Model identification. The stationary of variables was tested by augmented dickey fuller (ADF) test; Table 1 shows that all the variables have unit roots in levels and are stationary in first-differences as all values of ADF test are insignificant in levels, but significant at 1% level in both only intercept case, and trend and intercept case, which mean series become stationary.

4.1.2 Model estimation. We estimated various models in order to determine the right specification from BIC point of view, Table 2 reveals that ARIMA(1,1,1), ARIMA(2,1,2), ARIMA(1,1,0) ARIMA(1,1,2), ARIMA(0,1,0) and ARIMA(1,1,1) models are the most adequate fitted models to evaluate the price volatility of green beans, tomatoes, onions, oranges, grapes and strawberries, respectively.

Table 3 shows the parameter estimates of the ARIMA fitted model. The results show that most of the coefficients were significant at the 1% level. Lagged variables are important factors for producer decisions; Table 3 also shows that the producer response to lagged prices is statistically significant for all selected crops except green beans.

	Augmented Dickey–Fuller (ADF)			
	Log level		Log difference	
	Intercept	Trend and intercept	Intercept	Trend and intercept
Green beans	0.043	−2.344	−7.380***	−7.503***
Potatoes	−1.393	−1.508	−9.944***	−10.019***
Tomatoes	−0.604	−3.0.81	−8.316***	−8.223***
Onion	−0.893	−1.504	−10.69***	−10.623***
Oranges	−2.019	−0.218	−7.009***	−7.666***
Grapes	−1.388	−1.167	−5.611***	−5.705***
Strawberries	−0.415	−2.497	−4.669***	−4.556***

Note(s): *** indicates statistical significance at 1% level, **significance at 5% level and * significance at 10% level

Source(s): Compiled by researcher from unit root test depending on e-views. See Table A1 in appendix, http://www.fao.org/faostat/en/#data/PP

Table 1. Results of Augmented Dickey–Fuller (ADF) test

4.1.3 Diagnostic checking. There are no spikes outside the insignificant zone for both autocorrelation function and partial autocorrelation function residuals squared plot, we can conclude that residuals are white noise; hence, our ARIMA models are fitted. See Figure A1-A6 in appendix.

4.2 ARCH–GARCH model

4.2.1 Testing of ARCH effect. A fundamental assumption of the Box–Jenkins method is that the residuals remain constant over time (Jordaan *et al.*, 2007). Table 4 reveals the results of the ARCH-LM tests, the results of the test revealed the presence of ARCH effect only in potatoes crop case; hence we need to apply the GARCH approach. Keep in mind that the volatility in the agricultural prices of all the other crops remains constant over time.

4.2.2 Applying the GARCH approaches. In this study both akaike information criterion (AIC) and bayesian information criterion (BIC) were employed to select an appropriate GARCH model for potatoes. Table 5 displays the summaries of the AIC and BIC of different GARCH models. Therefore, GARCH (1,1) model is the best volatility models for the prices of potatoes. Table 6 shows estimation results of GARCH (1,1) model for potatoes price.

4.2.3 Model diagnostics GARCH (1,1) model for potatoes price. The ARCH-LM test was 1.251,189 under chi-square distribution for one lag difference of residuals squared, and the null hypothesis was not rejected. On the other hand, *F*-statistic was 1.230,710 and the test also not rejected the null hypothesis at the same condition. The results of the test indicated that the ARCH effect in potatoes' price series was no longer present.

Also, there are no spikes outside the insignificant zone for both autocorrelation function and partial autocorrelation function plot of the residuals squared, and we can conclude that residuals are white noise; hence, our GARCH (1,1) model is fitted. See Figure A7 in appendix.

4.3 Forecasting values of the model's variables

The forecasted value for producer price of some export crops is given in Table 7. As seen from the table, all prices will still be increasing in the forecasted period from 2016 to 2030. Forecasted value for green beans will increase from 2589.17 pound/ton in 2016–9752.392 pound/ton in 2030; forecasted value for potatoes will increase from 2399.156 pound/ton in 2016–8928.388 pound/ton in 2030; forecasted value for tomatoes will increase from 1556.775 pound/ton in 2016–5052.167 pound/ton in 2030; forecasted value for onion will increase from 1119.612 pound/ton in 2016–4103.752 pound/ton in 2030; forecasted value for oranges will increase from 1211.640 pound/ton in 2016–4621.151 pound/ton in 2030;

Table 2. Comparison of ARIMA models' statistical results

	ARIMA model	AIC	BIC	SEE
	(1,1,0)	−0.654449	−0.575719	0.170849
	(1,1,1)	−0.698718	*−0.580623*	0.165440
Price of green beans	(2,1,1)	−0.651745	−0.492733	0.167582
	(1,1,2)	−0.675285	−0.517825	0.165760
	(0,1,1)	−0.535757	−0.457790	0.181372
	(1,1,0)	−0.098697	−0.019968	0.225576
	(0,1,1)	−0.098139	*−0.020172*	0.225735
Price of potatoes	(1,1,1)	−0.069454	0.048640	0.226612
	(2,1,0)	−0.050214	0.069046	0.228655
	(0.1.2)	−0.059767	0.057183	0.227853
	(0,1,0)	−0.073934	0.004033	0.228483
	(2,1,1)	−0.109701	0.049311	0.219751
Price of tomatoes	(0,1,2)	−0.093246	0.023704	0.224071
	(2,1,2)	−0.207549	*−0.008784*	0.207241
	(2,1,0)	−0.095961	0.023298	0.223484
	(1,1,0)	−0.325772	*−0.247045*	0.201365
	(0,1,1)	−0.316133	−0.238166	0.202424
Price of onion	(1,1,1)	−0.290233	0.172139	0.202928
	(2,1,1)	−0.257396	−0.098384	0.204108
	(2,1,3)	−0.406647	−0.168129	0.185850
	(1,1,3)	−1.311786	−1.114962	0.119436
	(3,1,1)	−1.357026	−1.156285	0.116523
Price of oranges	(1,1,1)	−1.312217	−1.194122	0.121736
	(2,1,1)	−1.329224	−1.170211	0.119430
	(1,1,2)	−1.354267	*−1.196808*	0.118043
	(0,1,0)=(1,0,0)	−1.376484	*−1.298517*	0.119127
	(1,1,0)	−1.343734	−1.265004	0.121042
Price of grapes	(0,1,1)	−1.365305	−1.287338	0.119794
	(1,1,1)	−1.317650	−1.199556	0.121406
	(2,1,3)	−1.394781	−1.156263	0.113394
	(0,1,0)	−2.483603	−2.385432	0.067187
	(1,1,0)	−2.426575	−2.327837	0.068997
Price of strawberries	(0,1,1)	−2.476709	−2.378538	0.067399
	(1,1,1)	−2.590858	−2.442750	0.062354
	(2,1,0)	−2.355158	−2.206379	0.069978

Note(s): The criterions to judge for the best model are: (1) relatively small of BIC; (2) relatively small of SEE
Source(s): Compiled by researcher depending on e-views, See table A1 in appendix http://www.fao.org/faostat/en/#data/PP

forecasted value for grapes will increase from 3340.546 pound/ton in 2016–7411.219 pound/ton in 2030; forecasted value for strawberries will increase from 2659.23 pound/ton in 2016–6316.64 pound/ton in 2030.

We also note that the growth rate of forecasted prices for oranges, green beans, potatoes and onions, respectively is more than the growth rate of other selected crops, so it is expected during the forecast period the production and exports of oranges, green beans, potatoes and onions will increase at increasing rate, and will be more attractive for agricultural producers and exporters compared to tomatoes, grapes and strawberries, but this result depend on some facts which are:

(1) The rise in the prices of food commodities is reflected in the cropping pattern and the orientation of agricultural resources toward the production of high-priced food crops. (FAO. 1987)

Crop	Variable	Coefficient	Crop	Variable	Coefficient
Green beans	C	0.105307*** (0.020331)	onion	C	0.092780*** (0.020489)
	AR(1)	0.415593 (0.253390)		AR(1)	−0.433562*** (0.134097)
	MA(1)	−0.533474* (0.253390)			
Tomatoes	C	0.084106*** (0.004669)	Oranges	C	0.095622*** (0.033818)
	AR(1)	−0.235949* (0.134240)		AR(1)	0.836817*** (0.204140)
	AR(2)	0.587483*** (0.124705)			
	MA(1)	0.002845 (0.056911)		MA(1)	−0.941907 (0.237210)***
	MA(2)	−0.997075*** (0.056696)		MA(2)	0.250431 (0.151468)
Grapes	C	11.95011*** (4.480532)	Strawberries	C	0.061796*** (0.004029)
	AR(1)	0.983506*** (0.011885)		AR(1)	0.553773*** (0.216238)
				MA(1)	−0.999812*** (0.164080)

Note(s): Numbers in parenthesis are standard error
*** indicates statistical significance at 1% level, **significance at 5% level and * significance at level 10% level
Source(s): Compiled by researcher depending on e-views, See Table A1 in appendix, http://www.fao.org/faostat/en/#data/PP

Table 3.
Estimation results of fitted ARIMA models

Crop	Obs*R squared	p-value	F-statistic	p-value
Green beans	0.058240	0.8093	0.055778	0.8144
Potatoes	12.12621	0.0005***	15.64726	0.0003***
Tomatoes	0.058312	0.8092	0.055793	0.8144
Onion	1.451642	0.2283	1.433777	0.2376
Oranges	0.080358	0.7768	0.076999	0.7827
Grapes	0.237142	0.6263	0.228202	0.6352
Strawberries	0.003756	0.9511	0.003415	0.9540

Note(s): *** indicates statistical significance at 1% level
Source(s): Compiled by researcher depending on e-views, See Table A1 in appendix, http://www.fao.org/faostat/en/#data/PP

Table 4.
ARCH- LM test summary statistics

	GARCH (1,1)	GARCH (1,2)	GARCH (2,1)	GARCH (2,2)
AIC	−0.233753	−0.191402	−0.124254	−0.175014
BIC	−0.077820	0.003515	0.070663	0.058887

Source(s): Compiled by researcher depending on e-views, See Table A1 in appendix, http://www.fao.org/faostat/en/#data/PP

Table 5.
GARCH model selection for Potatoes using AIC and BIC

(2) The rewarding prices stimulate agricultural investment which is the main driver for sustainable agricultural development, where increasing investment means adding new production projects that lead to absorption a number of unemployed workers, in addition to increasing production, exports, then improving the trade balance. (Syed and Miyazako, 2013)

(3) Egypt already has comparative advantage of the selected crops in many foreign markets.

(4) There are several macroeconomic factors affecting the volatility of food commodity prices that must be taken into consideration such as: productivity, climate change,

	Coefficient	Standard error	z-statistic	Prob
Mean equation				
Constant	0.093866***	0.020949	4.480667	0.0000
Variance equation				
Constant	0.035902***	0.011137	3.223592	0.0013
RESID(−1)^2	0.413,469***	0.203434	2.032450	0.0421
GARCH(−1)	−0.333,808	0.280911	−1.188305	0.2347
ARCH-LM test				
F-statistic	1.230710 (0.2732)			
Obs*R-squared	1.251189 (0.2633)			

Note(s): - Numbers in parenthesis are p-value, *** indicates statistical significance at 1% level
Source(s): Compiled by researcher depending on e-views, See Table A1 in appendix, http://www.fao.org/faostat/en/#data/PP

Table 6. Estimation results of GRACH (1,1) model for potatoes price

year	Green beans	Potatoes	Tomatoes	Onion	Oranges	Grapes	Strawberries
2016	2589.17	2399.156	1556.775	1119.612	1211.640	3340.546	2659.23
2017	2846.429	2635.262	1692.235	1228.461	1333.211	3558.747	2828.75
2018	3129.246	2894.604	1841.824	1347.892	1466.981	3787.247	3009.07
2019	3440.163	3179.468	2002.359	1478.934	1614.175	4026.283	3200.88
2020	3781.972	3492.366	2179.098	1622.717	1776.139	4276.087	3404.93
2021	4157.742	3836.058	2369.286	1780.478	1954.355	4536.884	3621.98
2022	4570.849	4213.572	2578.163	1953.576	2150.455	4808.888	3852.86
2023	5025.001	4628.239	2803.423	2143.504	2366.233	5092.307	4098.47
2024	5524.277	5083.714	3050.339	2351.896	2603.662	5387.339	4359.73
2025	6073.160	5584.013	3317.083	2580.548	2864.917	5694.173	4637.64
2026	6676.579	6133.548	3609.017	2831.430	3152.387	6012.985	4933.27
2027	7339.953	6737.163	3924.832	3106.702	3468.703	6343.945	5247.75
2028	8069.239	7400.182	4270.043	3408.737	3816.759	6687.209	5582.27
2029	8870.985	8128.450	4643.907	3740.135	4199.740	7042.922	5938.11
2030	9752.392	8928.388	5052.167	4103.752	4621.151	7411.219	6316.64

Source(s): Calculated by researcher depending on e-views
http://www.fao.org/faostat/en/#data/PP

Table 7. Forecasted values of producer price of some export crops in Egypt from 2016 to 2030 pound/ton

agricultural policy adjustments, large government purchases, and from outside the agricultural sector: exchange rate, variation in oil price and trade policies (El-Rasoul and Tolba, 2018).

(5) Future policy options will concentrate on increasing the efficiency of water usage and keeping the sustainability of both land and water. (Abdou Abdelaal and Thilmany, 2019)

Then forecasting agricultural prices is an essential requirement for decision-makers to develop suitable agricultural policies in both short and long term, in the fields of production, consumption, marketing and trade (Lama *et al.*, 2015; Solanki and Sharma, 2016).

Furthermore, it is also relevant for the private sector to study the differences in price volatility among products for production and marketing decision (Heifner and Kinoshita, 1994; Jordaan *et al.*, 2007). On the other hand, several study results indicated that agricultural price variability has a major impact on food security (El-Rasoul and Tolba, 2018), so it is extremely necessary to provide decision-makers with a database of future agricultural price to deal with any food crisis.

5. Conclusion

Commodity prices are subject to high degrees of volatility, especially the prices of agricultural commodities. Production decisions and risk-management require the producers, traders and policy-makers to have good knowledge about the trend and reasons of agricultural commodity price volatility (Riazi, 2016).

This study focuses on forecasting the prices of the most important export crops of vegetables and fruits in Egypt using ARIMA model and GARCH model from 2016 to 2030.

The results show that ARIMA (1,1,1), ARIMA (2.1,2), ARIMA (1,1,0) ARIMA (1,1,2), ARIMA (0,1,0) and ARIMA (1,1,1) models are the most appropriate fitted models to evaluate the volatility of price of green beans, tomatoes, onions, oranges, grapes and strawberries, respectively. The results also revealed the presence of ARCH effect only in the case of potatoes, hence it is suggested that the GARCH approach be used instead. The GARCH (1,1) was found to be a better model in forecasting price of potatoes. The results revealed that all the forecasted prices of selected crops will still be increasing in the forecasted period from 2016 to 2030.

We also note that the growth rate of forecasted prices for oranges, green beans, potatoes and onions, respectively is more than the growth rate of other selected crops, so it is expected during the forecast period the production and exports of oranges, green beans, potatoes and onions will increase at increasing rate, and will be more attractive for agricultural producers and exporters compared to tomatoes, grapes and strawberries.

The study recommends more studies in the field of forecasting in terms of prices, production and trade, production costs for other agricultural crops that lead to have a database on the future status of Egyptian agriculture that helps agricultural producers and investors as well as it helps decision-makers in drawing different agricultural policies.

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Appendix

The Appendix files are available online for this article.

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