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Effectiveness of price forecasting techniques for capturing asymmetric volatility for onion in selected markets of Delhi

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ABSTRACT

Onion prices exhibit very high instability/volatility in all the selected markets of Delhi. The present study aimed to forecast the prices of onion for three markets of Delhi, viz. Azadpur, Keshopur and Shahdara using different foresting techniques. The study was based on times series secondary data on monthly wholesale price of onion from April 2005 to February 2015. After ensuring the stationarity of series after seasonal adjustment and differencing, the best ARIMA model was chosen for individual series. The residuals were checked for the presence of autocorrelation, it was found that the residuals are correlated implying improper specification of the models. Also, the plots of prices in the selected markets also exhibited nonlinearity in the series, which necessitated the application of non-linear models to the data. Considering this, squared residuals were checked for the presence of conditional heteroscedasticity. The presence of conditional heteroscedasticity was found in all the three price series. A significant ARCH-LM test and high value of skewness and kurtosis coefficients justify the selection of EGARCH models as the best fit models in these markets. The out-of-sample forecast of onion price has been carried out by using the best fitted EGARCH/ GARCH model and it is projected that the prices of onion will be between ₹1800-1950 per quintal in Azadpur and Shahdara market; while the prices will remain between ₹ 2178 to 2413 per quintal in Keshopur market during March to July, 2015.

Key words: EGARCH model, GARCH model, Onion, Onion prices, Volatility

Onion production in the country has consistently increased, spectacular productivity driven growth has been noticed in the onion production after 2002-03. India produced 19.4 million tonnes of onion from acreage of 1.2 million ha in 2013-14. Close to 70% of onion supply comes from Maharashtra, Madhya Pradesh, Karnataka, Gujarat, Bihar and Andhra Pradesh. Maharashtra is the leading state accounting for 30 per cent of onion production. The supply scenario in major producing states creates major impact on the onion prices and vice-versa. Thus, proper understanding of agricultural price mechanism and their forecast would help farmers to plan the production portfolio and marketing for improved farm profit. The sufficient information about the price forecasts would strengthen the otherwise weak linkage between production and marketing in the country.

As far as time series forecasting is concerned, Box Jenkins Autoregressive Integrated Moving Average (ARIMA) model has been dominated in the literature. There are lot of applications in agriculture. To cite a few, Paul and Das (2010, 2013) applied ARIMA model for modelling and forecasting of Inland fish production in India as well as fish landing in Ganga basin. Paul *et al.* (2013) applied Seasonal ARIMA (SARIMA) model for forecasting of total meat export from India. Paul *et al*. (2014, 2015) attempted forecasting wholesale and retail price of pegion pea in different markets of India. But one drawback of ARIMA model is that it cannot capture the volatile behaviour of the series. The most widely used nonlinear models for capturing the volatility in a series are Autoregressive Conditional Heteroscedastic (ARCH) model (Engle 1982) and Generalized ARCH (GARCH) model (Bollerslev 1986). Paul *et al*. (2011, 2014) have applied GARCH model for modelling and forecasting of volatile data. However, sometimes, the volatility due to positive and negative shocks is asymmetric. To this end, Nelson (1991) proposed the Exponential GARCH (EGARCH) model. A good description of these models is given by Fan and Yao (2003) and Tsay (2005). Ghosh *et al*. (2013) applied EGARCH model for forecasting India's fruits and vegetables seeds export.

Since Delhi is the major consuming and distributing market for onion, the present study aimed to forecast the prices of onion for three markets of Delhi, viz. Azadpur, Keshopur and Shahdra using different foresting techniques. The study also attempted to compare and contrast the results of different quantitative forecasting techniques so as to understand the suitability of these techniques in case of

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Onion. It is expected that findings of the study would be helpful to understand the applicability and accuracy of these techniques under different scenarios.

MATERIALS AND METHODS

The study was based on times series secondary data on monthly wholesale price of onion from April 2005 to February 2015, i.e. 119 observations for each selected market, complied from AGMARKNET website. Out of the 119 observations, first 107 observations have been used for model building and remaining 12 observations have been used for model validation. Quantitative techniques like ARIMA, ARCH, and GARCH models were used to develop the forecast. A brief description of the models used is given below.

Said and Dickey (1984) augment the basic autoregressive unit root test to accommodate general ARMA(p, q) models with unknown orders and their test is referred to as the augmented Dickey- Fuller (ADF) test. The ADF test tests the null hypothesis that a time series y_t is nonstationary against the alternative that it is stationary, assuming that the dynamics in the data have an ARMA structure. The ADF test is based on estimating the test regression

$$\Delta y_t = \beta' D_t + \pi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t$$

where D_t is a vector of deterministic terms (constant, trend etc.). The p lagged difference terms, Δy_{t-j}, are used to approximate the ARMA structure of the errors, and the value of p is set so that the error ε_t is serially uncorrelated. The error term is also assumed to be homoscedastic. Under the null hypothesis, Δy_t is I(0) which implies that $\pi = 0$. The ADF t-statistic is then the usual t-statistic for testing $\pi = 0$.

Seasonal adjustment is a statistical method for removing the seasonal component of a time series that exhibits a seasonal pattern. Many agricultural phenomena have seasonal cycles, such as agricultural production and price of commodity. It is necessary to adjust for this component in order to understand what underlying trends are in the series. Unlike the trend and cyclical components, seasonal components, theoretically, happen with similar magnitude during the same time period each year. The seasonal components of a series are sometimes considered to be uninteresting and to hinder the interpretation of a series. Removing the seasonal component directs focus on other components and will allow better analysis. The popular method of seasonal adjustment is X-12-ARIMA developed by the United States Census Bureau. In the present investigation this method has been used for seasonal adjustment of the price series

A generalization of Autoregressive Moving Average (ARMA) models which incorporates a wide class of non-stationary time-series is obtained by introducing the differencing into the model. This is the simplest example of a non-stationary process which reduces to a stationary one after differencing is Random Walk. A process $\{y_t\}$ is said to follow an Integrated ARMA model, denoted by ARIMA (*p*, *d*, *q*), if $\nabla^d y_t = (1-B)^d \varepsilon_t$ is ARMA (*p*, *q*). The model is written as Equation (1):

$$\varphi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \qquad (1)$$

where, $\varepsilon_t \sim WN(0, \sigma^2)$, and *WN* indicates white noise. The integration parameter *d* is a nonnegative integer. When $d = 0$, ARIMA $(p, d, q) \equiv$ ARMA (p, q).

The ARIMA methodology is carried out in three stages, viz. identification, estimation and diagnostic checking. Parameters of the tentatively selected ARIMA model at the identification stage are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory. ARIMA model is selected for the time-series under consideration. An excellent discussion of various aspects of this approach is given in Box *et al*. (2007). Most of the standard software packages, like SAS, SPSS and EViews contain programs for fitting of ARIMA models.

Let $\varepsilon_t = y_t - \phi y_{t-1}$ be the residual series. The squared series $\{\varepsilon_t^2\}$ is then used to check for conditional heteroscedasticity, which is also known as the ARCH effects. Two tests are available. The first one is to apply the usual Ljung-Box statistic $Q(m)$ to the $\{\varepsilon_t^2\}$ series. The null hypothesis is that the first *m* lags of autocorrelation functions of the $\{\varepsilon_t^2\}$ series are zero. The second test for conditional heteroscedasticity is the Lagrange multiplier test of Engle (1982). This test is equivalent to usual *F*-statistic for testing $H_0 : a_i = 0, i = 1, 2, ..., q$ in the linear regression

$$\varepsilon_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + ... + a_q\varepsilon_{t-q}^2 + e_t, \; t = q+1, ..., T \qquad (2)$$

where, e_t denotes the error term, *q* is the pre-specified positive integer, and *T* is the sample size. Let $SSR_0 = \sum_{t=q+1}^{T} (\varepsilon_t^2 - \varpi)^2$, where $\varpi = \sum_{t=q+1}^{T} \varepsilon_t^2 / T$ is the sample mean of $\{e_t^2\}$, and $SSR_1 = \sum_{t=q+1}^{T} \hat{e}_t^2$, where $\hat{e}_t$, is the least squares residual of (2). Then, under H_0,

$$F = \frac{(SSR_0 - SSR_1)/q}{SSR_1\,(T-q-1)} \qquad (3)$$

is asymptotically distributed as chi-squared distribution with *q* degrees of freedom.

The ARCH(*q*) model for the series $\{\varepsilon_t\}$ is defined by specifying the conditional distribution of ε_t given the information available up to time *t*-1. Let ψ_{t-1} denote this information. ARCH (*q*) model for the series is given by

$$et/\psi_{t-1} \sim N(0, h_t) \qquad (4)$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \qquad (5)$$

where, $a_0 > 0$, $a_i > 0$ for all *i* and $\sum_{i=1}^{q} a_i < 1$ are required to be satisfied to ensure non-negative and finite unconditional variance of stationary $\{\varepsilon_t\}$ series.

But when the order of ARCH model is very large, estimation of a large number of parameters is required. Also, the conditional variance of ARCH(q) model has the property that unconditional autocorrelation function (ACF) of squared residuals; if it exists, decays very rapidly compared to what is typically observed, unless maximum lag q is large. To overcome the weaknesses, Bollerslev (1986) proposed the Generalized ARCH (GARCH) model in which conditional variance is also a linear function of its own lags and has the following form:

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j} \tag{6}$$

$a_0 > 0,\ a_i > 0,\ i = 1, 2, ..., q. \quad b_j > 0,\ j = 1,2, ..., p$

The GARCH (p, q) process is weakly stationary if and only if

$$\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} b_j < 1$$

The EGARCH model was developed to allow for asymmetric effects between positive and negative shocks on the conditional variance of future observations. Another advantage, as pointed out by Nelson and Cao (1992), is that there are no restrictions on the parameters. In the EGARCH model, the conditional variance, h_t, is an asymmetric function of lagged disturbances. The model is given by

$$\varepsilon_t = \xi_t h_t^{1/2}, \quad \ln(h_t) = a_0 + \frac{1 + b_1 B + ... + b_{q-1} B^{q-1}}{1 - a_1 B + ... + a_p B^p} g(\varepsilon_{t-1}) \tag{7}$$

where,

$$g(\varepsilon_t) = \begin{cases} (\theta + \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|), & if\ \varepsilon_t \geq 0, \\ (\theta - \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|), & if\ \varepsilon_t < 0, \end{cases}$$

B is the backshift (or lag) operator such that $Bg(\varepsilon_t) = g(\varepsilon_{t-1})$

The EGARCH model can also be represented in another way by specifying the logarithm of conditional variance as

$$\ln(h_t) = a_0 + \beta \ln(h_{t-1}) + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{8}$$

This implies that the leverage effect is exponential, rather than quadratic, and the forecasts of the conditional variance are guaranteed to be non-negative.

The EGARCH model in (8) shows some differences from the standard GARCH model: (i) Volatility of the EGARCH model, which is measured by the conditional variance h_t, is an explicit multiplicative function of lagged innovations. On the contrary, volatility of the standard GARCH model is an additive function of the lagged error terms, which causes a complicated functional dependency on the innovations. (ii) Volatility can react asymmetrically to the good and bad news. (iii) For the general distributions of the parameter restrictions for strong and covariance-stationarity coincide. (iv) The parameters in EGARCH model are not restricted to positive values.

The function $g(.)$ in (7) is piecewise linear. It contains two parameters which define the 'size effect' and the 'sign effect' of the shocks on volatility. The first is a typical ARCH effect while the second is an asymmetrical effect, for example, the leverage effect. The term determines the size effect and the term determines the sign effect. The parameter is thus typically positive and is negative.

For estimating parameters of GARCH model, most widely used method is the Gaussian maximum likelihood estimation (GMLE) method. For estimation of conditionally heteroscedastic time-series models from a mathematically rigorous perspective, Straumann (2005) may be referred. Huang *et al*. (2008) discussed situations under which a particular estimation procedure should be used. However, no method can be called as the "Best". Evidently, the above procedures are computationally very cumbersome. In the present investigation, SAS software version 9.3 has been used for data analysis.

RESULTS AND DISCUSSION

Onion arrival pattern in Delhi

In India, onion is grown in three crop seasons, namely *kharif* (harvested in October-November), late *kharif* (January February) and *rabi* (April – May). *Rabi* season crop is the largest accounting for about 60% of annual production with kharif and late *kharif* accounting for about 20 percent each. Delhi markets receive both the *kharif* and *rabi* arrivals from the producing locations. Delhi is a major consuming market for onions, which is evident from the fact that arrivals in Delhi as a percent to arrivals in the markets of major producing states are considerable (Table 1). The arrivals in Delhi have increased significantly in 2013 and 2014. The increase has been such that total arrivals in Delhi markets have exceeded the total arrivals of Madhya Pradesh in the recent years. The distribution shift in Delhi markets has also been noticed. Earlier the onion trade in Delhi was predominantly confined to Azadpur mandi, whereas Shahdara mandi has now emerged as the major market in Delhi for onion trade (Table 1).

Table 2 briefs the descriptive statistics of the markets selected for the study. It can be inferred from the table that there was no significant difference in the average price of onion across the three markets which was between ₹ 10 to 12 per kg during the study period. However, a high instability/volatility was observed in the prices of onion over time as evident from the high value of the coefficient of variation which remained around 70 percent in each of these markets. The prices of onion varied from as low as ₹ 280 per quintal in Shahdara in May 2006 to as high as ₹ 5412 per quintal in Keshopur in September 2013. Among the three markets Keshopur market exhibited the highest deviation in prices.

The value of kurtosis coefficient was the highest in Azadpur market closely followed by Keshopur and Shahdra markets. This means that the data follows a leptokurtic distribution and there is high probability for extreme values.

Table 1 Arrival pattern of onion in major producing and consuming states

Year	Delhi			Delhi arrival as % to			
	Azadpur	Keshopur	Shahdara	Total	MH	MP	Kar
2011	314	24	38	375	12	83	39
2012	333	24	34	391	10	55	41
2013	287	45	556	887	30	171	80
2014	281	108	374	762	22	114	60

Table 2 Descriptive statistics of onion prices of selected markets

Market	Mean (₹/quintal)	SD	Minimum	Maximum	Kurtosis	Skewness	CV
Azadpur	1018	699	330	4606	10	3	68.64
Keshopur	1188	821	324	5412	9	3	69.11
Shahdara	1037	749	280	4749	8	3	72.30

The data exhibits a considerable degree of skewness as indicated by its coefficient value which was 3 in case of all markets indicating asymmetry in the data.

Seasonality in onion prices

Delhi markets receive both the *kharif* and *rabi* arrivals from the producing locations The *kharif* arrival starts in the month of October and continues up to March, while the *rabi* arrivals are available from April to June. The same can be observed through the seasonal indices of prices of onion computed for the three markets (Table 3). A perusal of Table 3 indicates that the prices of onion remained above average price in the months from August to January. Whereas, these indices remained below the average price in the months from February to July. The highest and the lowest prices were witnessed in the month of October and May in all the three markets. The influence of seasonality in the data has been eliminated by adjusting them with seasonal indices. A graphical representation of the data for the three markets with and without the presence of seasonality component is presented in the Fig 1.

Stationarity and ARCH tests

The results of Augmented Dickey Fuller (ADF) on original data series revealed that the data series was non-stationary for all the three markets. In order to make the data series stationary, the original series was adjusted for seasonality and then the differencing of resultant series was series was done at one lag. Results of ADF test, used to test the stationary of seasonally adjusted series, are presented in Table 4. The presence of unit root is noticed in the seasonally adjusted series, whereas the hypothesis of presence of unit root is rejected in the differenced series at 5 percent level of significance.

Table 3 Seasonal factor for onion prices in the selected markets

Month	Azadpur	Keshopur	Shahdara
January	1.1821	1.1198	1.2889
February	0.9376	0.9613	1.0826
March	0.7945	0.8192	0.8444
April	0.7198	0.6855	0.7004
May	0.6508	0.6049	0.6367
June	0.7029	0.7270	0.7083
July	0.9617	0.9737	0.9706
August	1.1508	1.1715	1.0763
September	1.3085	1.3256	1.1672
October	1.4932	1.5698	1.4701
November	1.3578	1.3599	1.2821
December	1.1745	1.1653	1.1693

Application of forecasting models

After ensuring the stationarity of series after seasonal adjustment and differencing, the best ARIMA model was chosen for individual series. The residuals were checked for the presence of autocorrelation, it was found that the residuals are correlated implying improper specification of the models. The plots of prices in the selected markets (Fig 1) also exhibited nonlinearity in the series, which indicated that no linear model can fit the data properly. Considering this, squared residuals were checked for the presence of conditional heteroscedasticity. It is evident from the Table 5 that there is presence of conditional heteroscedasticity in all the three price series.

An uncorrelated time series can still be serially dependent due to a dynamic conditional variance process. A time series exhibiting conditional heteroscedastic or autocorrelation in the squared series is said to

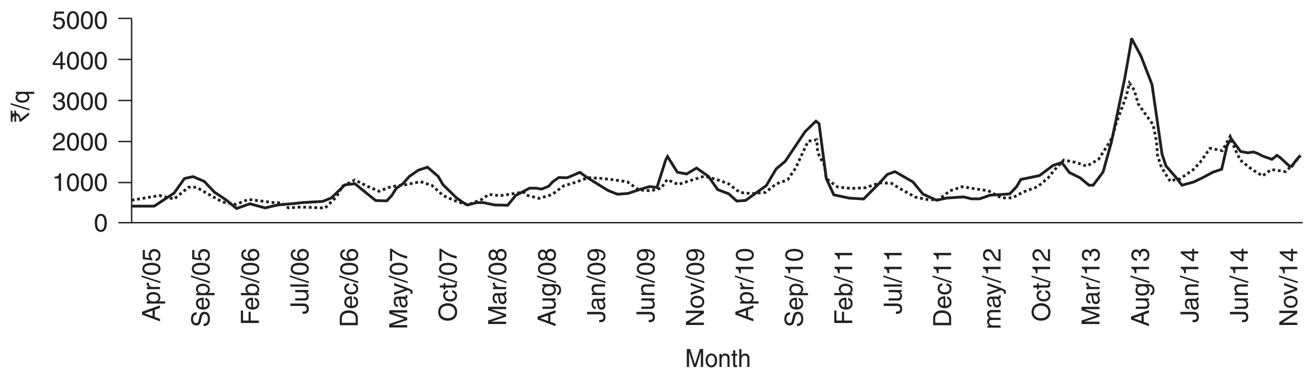

Fig 1 Actual price series (Black line) and seasonally adjusted series (dashed line) for Azadpur market

Table 4 Augmented Dickey Fuller (ADF) test results

Market	Test statistic	
	Seasonally adjusted series	1st difference of seasonally adjusted series
Azadpur	–2.177	–7.037
Keshopur	–2.194	–7.815
Shahdara	–2.488	–7.367

Note: 5% critical value is -2.8870

have autoregressive conditional heteroscedastic (ARCH) effects. Engle's ARCH test was a Lagrange multiplier test to assess the significance of ARCH effects. The perusal of test results in Table 6 reveals that the test statistic was found to be significant at 1 percent level of significance and hence leads to rejection of null hypothesis in all the three markets. The tests are significant ($p<0.0001$) through order 12, which indicates that a very high-order ARCH model is needed to model the heteroscedasticity. As GARCH model is parsimonious than ARCH model, in the present investigation GARCH model and its extension like EGARCH model have been applied.

The parameter estimates of best fitted models in each of three markets along with their standard error and level of significance are presented in Table 6. It is clearly evident that the parameters of ARIMA(1,1,0)-EGARCH(1,1) model, which is the best fit in Azadpur market, are significant at 1 per cent level of significance with least standard error values as compared to best fit models in other markets. A significant ARCH-LM test and high value of skewness and kurtosis coefficients also justify the selection of EGARCH models as the best fit models in these markets. The mean model AR (1) parameter value of 0.3211 in case of ARIMA (1,1,0)-EGARCH(1,1) model for Keshopur market explains the highest degree of variability in the data as compared to other mean model parameters.

Validation of forecasting models and onion price forecasts

Validation of the model is an important criterion for its selection. In order to validate the model, from the total 119 data points in each market, the first 107 data points corresponding to period April 2005 to February 2014 were used for building the model and the remaining 12 data points corresponding to period February 2014 to February 2015 were used for validation purpose.

A comparative picture of the relative mean absolute error (RMAPE) values of the best fitted models in each category is presented in Table 7. It can be inferred from the Table that the volatility in the onion prices could be captured best by the ARIMA(1,1,0)-EGARCH(1,1) model in case of Azadpur and Keshopur exhibiting a RMAPE value of 21.9 and 20.7, respectively. Whereas, in case of Shahdra market, ARIMA (1,1,0)-GARCH (1,1) was found to be the best fit with a RMAPE of 23.06. In none of the cases, ARIMA was found as a better fit, thereby, indicating that the GARCH models are better suited to volatility in the data. The conditional standard deviations of fitted EGARCH and GARCH models have been plotted in Fig 2, 3. Here, x axis represents year and y axis represents price in ₹/q. A perusal of Fig 4 to 6 indicates strong volatility in the onion price in all the markets.

The out-of-sample forecast of onion price has been carried out by using the best fitted EGARCH/GARCH model and the same is reported in Table 8. It is expected that the price will remain high in Keshopur market in comparison to other two markets. Also the onion price in Azadpur and Shahdara will remain almost same.

Onion prices exhibit very high instability/volatility in all the selected markets of Delhi. For the purpose of price forecasting of onion, the best ARIMA model was chosen for individual series after ensuring the stationarity of the price series after seasonal adjustment and differencing. The residuals were checked for the presence of autocorrelation, it was found that the residuals are correlated implying improper specification of the models. Also, the plots of prices in the selected markets also exhibited nonlinearity in the series, which necessitated the application of non-linear models to the data. Considering this, squared residuals were checked for the presence of conditional heteroscedasticity.

Table 5 Tests for ARCH disturbances based on ARIMA residuals

Order	Azadpur market				Keshopur market				Shahdara market			
	Q	Pr > Q	LM	Pr > LM	Q	Pr > Q	LM	Pr > LM	Q	Pr > Q	LM	Pr > LM
1	77.4	<.0001	72.5	<.0001	77.0	<.0001	72.1	<.0001	77.8	<.0001	72.9	<.0001
2	97.2	<.0001	86.6	<.0001	97.5	<.0001	84.9	<.0001	97.7	<.0001	87.6	<.0001
3	98.0	<.0001	87.0	<.0001	98.4	<.0001	85.0	<.0001	98.5	<.0001	88.2	<.0001
4	98.3	<.0001	87.6	<.0001	98.8	<.0001	85.5	<.0001	98.9	<.0001	88.4	<.0001
5	98.9	<.0001	88.6	<.0001	99.5	<.0001	85.8	<.0001	99.7	<.0001	88.7	<.0001
6	99.6	<.0001	88.6	<.0001	100.0	<.0001	85.8	<.0001	100.2	<.0001	88.7	<.0001
7	100.2	<.0001	88.8	<.0001	100.4	<.0001	85.9	<.0001	100.4	<.0001	88.8	<.0001
8	100.4	<.0001	88.8	<.0001	100.6	<.0001	86.0	<.0001	100.5	<.0001	88.8	<.0001
9	100.5	<.0001	88.8	<.0001	100.8	<.0001	86.0	<.0001	100.5	<.0001	88.8	<.0001
10	100.5	<.0001	88.9	<.0001	100.9	<.0001	86.0	<.0001	100.5	<.0001	88.8	<.0001
11	100.6	<.0001	89.2	<.0001	101.0	<.0001	86.0	<.0001	100.5	<.0001	88.9	<.0001
12	100.6	<.0001	89.3	<.0001	101.1	<.0001	86.0	<.0001	100.6	<.0001	88.9	<.0001

Table 6 Parameter estimates of the best fit models

Parameter	Coefficient	Std. error	z-Statistic	Prob.
Parameter estimate of ARIMA(1,1,0)-EGARCH(1,1) model for Azadpur				
C	23.834	23.304	1.0227	0.3064
AR(1)	0.2904	0.0785	3.6988	0.0002
Variance equation				
C	0.7331	0.2948	2.4872	0.0129
|RES|/SQR [GARCH](1)	-0.0551	0.0694	-0.7937	0.4274
RES/SQR [GARCH](1)	0.3721	0.0974	3.8219	0.0001
EGARCH(1)	0.9342	0.0253	36.964	<0.0001
Parameter estimate of ARIMA(1,1,0)-EGARCH(1,1) model for Keshopur				
C	40.285	28.994	1.3894	0.1647
AR(1)	0.3211	0.0680	4.7212	<0.0001
Variance equation				
C	0.9640	0.4758	2.0262	0.0427
|RES|/SQR [GARCH](1)	-0.1927	0.1085	-1.7759	0.0758
RES/SQR [GARCH](1)	0.5626	0.1430	3.9334	<0.0001
EGARCH(1)	0.9236	0.0385	23.969	0.0001
Parameter estimate of ARIMA(1,1,0)-GARCH(1,1) model for Shahdara				
C	21.833	29.110	0.7500	0.4532
AR(1)	0.2473	0.1242	1.9911	0.0465
Variance equation				
C	5812.1	4617.8	1.2586	0.2082
ARCH(1)	0.5926	0.2481	2.3881	0.0169
GARCH(1)	0.3275	0.1645	1.9914	0.0246

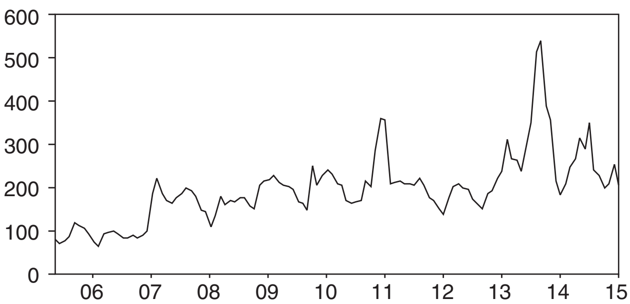

Fig 2 Conditional standard deviation of fitted EGARCH model for Azadpur market.

The presence of conditional heteroscedasticity was found in all the three price series. A significant ARCH-LM test and high value of skewness and kurtosis coefficients justify the selection of EGARCH models as the best fit models in these markets. The volatility in the onion prices could be captured best by the ARIMA(1,1,0)-EGARCH(1,1) model in case of Azadpur and Keshopur exhibiting a RMAPE value of 21.9 and 20.7, respectively. Whereas, in case of Shahdara market, ARIMA (1,1,0)-GARCH (1,1) was found to be the best fit with a RMAPE of 23.06. In none of the cases, ARIMA was

Table 7 RMAPE value (%) for different models in three markets

Market	ARIMA (1,1,0)	ARIMA(1,1,0)-GARCH(1,1)	ARIMA(1,1,0)-EGARCH(1,1)
Azadpur	26.61	25.96	21.91
Keshopur	30.40	51.92	20.72
Shahdara	30.57	23.06	30.82

Table 8 Onion price forecasts from March to July, 2015 (₹/q) in selected markets of Delhi

Month	Azadpur	Keshopur	Shahdara
Mar-15	1800	2178	1785
Apr-15	1858	2254	1823
May-15	1893	2312	1847
Jun-15	1922	2364	1868
Jul-15	1950	2413	1889

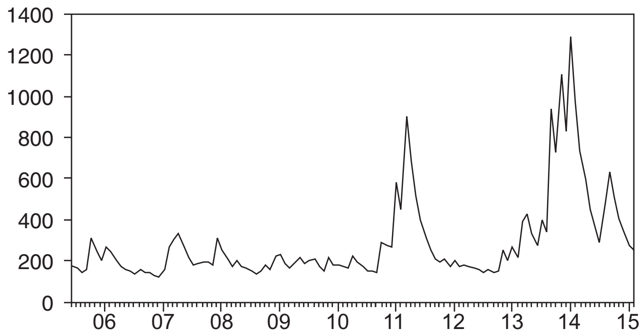

Fig 3 Conditional standard deviation of fitted GARCH model for Shahdara market.

found as a better fit, thereby, indicating that the GARCH models are better suited to volatility in the data. The out-of-sample forecast of onion price has been carried out by using the best fitted EGARCH/GARCH model and it is projected that the prices of onion will be between ₹ 1800-1950 per quintal in Azadpur and Shahdara market; while the prices will remain between ₹ 2178 to 2413 per quintal in Keshopur market during March to July, 2015. It is to note here that the price may vary due to extraneous factors like arrivals, climate conditions or any other causes.

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