The volatility spillover of potato prices in different markets of India

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Abstract

Agricultural commodity prices particularly the prices of perishable commodities are volatile in nature. The inter dependency of market prices of agricultural commodities makes it difficult for accurate modelling. In the present investigation, two variants of multivariate generalized autoregressive conditional heteroscedastic (MGARCH) models namely DCC and BEKK have been applied for modeling the price volatility of potato in five major markets in India i.e. Agra, Delhi, Bengaluru, Mumbai and Ahmedabad. It is observed that Agra market has the highest price variability whereas Mumbai has the least price variability. All the studied market prices showed significant presence of conditional heteroscedasticity. To this end, Volatility Impulse Response Function (VIRF) has been used to see the impacts of a specific shock on the price volatility spillovers of potato among the studied markets. The volatility spillover has been computed for all the markets.

Keywords: Potato price, Nonlinearity, Spillover, Volatility

Introduction

Value of agricultural commodities are influenced by fluctuations in price that arise from various factors including unfavorable weather conditions, natural disasters, shifts in demand and supply, change in agricultural policies and exchange rate volatility. Huge and unforeseen variations in price create a scene of unpredictability which increases risks for producers, traders, consumers and government. Bellemare *et al*. stated agricultural commodity price volatility has been exceptionally high during the last decade when food price volatility reached almost a 30-year high in December 2010[1]. The continuous fluctuations in prices of commodity has attracted interest and attention in field of economic and financial literature, it can also be viewed as one of the most important economic events[2]. Prices of commodity are generally volatile in nature and agricultural commodities are especially known for their continuously volatile nature[3]. Further, volatility of prices has a direct impact on competition by increasing consumer costs[4]. Apergis and Rezitis in their study observed that volatility of price brings up situation of uncertainty and risk for both producers and consumers[5]. It is established that extreme weather events do have large impact on volatility. Furthermore, with the application of the spillover index, it is possible to calculate the quantity of volatility spillovers across time. Candila and Farace in their study investigated the presence, the size, and the persistence of volatility spillovers among five agricultural commodities (corn, sugar, wheat, soybean, and bioethanol) and five Latin American (Argentina, Brazil, Chile, Colombia, Peru) stock market indexes[6]. The study also contributed towards the analysis that, in general, higher agricultural commodity volatilities may induce economic weakness, mainly in food-exporter countries. In Indian context, price volatility of agricultural commodities has been studied extensively in the past. Most studies of price volatility examined the volatility of commodity price in a specified market. Paul et al. studied export price volatility of spices from India[7]. Paul et al. examined price volatility and linkages between domestic & export prices of onion in India[8]. Paul et al. studied price volatility in food commodities in India[9]. Paul et al. investigated asymmetric price volatility for onion in selected markets of Delhi[10]. Singla et al. carried out study on modelling price volatility in onion hybrid models[11]. Furthermore, in turn, a more fragile economy can heavily undermine the food security. The concept of volatility impulse response analysis was coined by Hafner and Herwartz, which is built on the methodology of multivariate GARCH model[12]. The main aim of this method is the analysis of the conditional variance instead of the conditional mean. This analysis allows to visualize the behavior of the conditional volatility after a historical shock. Sinha et al. studied volatility spillover using MGARCH model for the price of Black Pepper[13]. Paul et al. applied different MGARCH models for modelling volatility as well studying spillover effect for onion prices in different markets of India[14].

India occupies the second position on the scale of largest producers of potatoes globally. India produces around 9.97% of world’s total potato production in 2017 (FAOSTAT). The vast growth in production of potatoes in India can be attributed to expansion in area than improvement in yield per hectare. Agricultural markets are one of the most important global markets because of their correlation not only with markets like energy markets, commodities or stock markets, but they also have an impact on political and social events.

The highest producer of potato in India is Uttar Pradesh (30.32% of total production), followed by West Bengal (24.91%), Bihar (14.23%), Madhya Pradesh (6.36%), Gujarat (6.22%) and others (24.52%) (Horticultural Statistics at a Glance 2018). The leading states in terms of area under potato are Uttar Pradesh, West Bengal, Bihar, Gujarat and Madhya Pradesh in total covering around 94% of total area. Area coverage under Rabi potato has increased slightly in India as compared to previous year. The production of potato during the year 2017-18 is estimated to be 5.57 % higher as compared to that of the previous year i.e. 2016-17. Harvesting of the crop is usually dependent on the weather conditions and market prospects. If the demand is higher in the market, harvesting is done slightly early. In short, potato can be concluded being a staple food as wheat and rice in India. Total demand of potatoes in India during 2017-18 was estimated to be 47.15 million tonnes. Other than this, India is also involved in exporting of potato and total export during the year 2017-18 was 395.75 thousand million tonnes (Horticultural Statistics at a Glance). Since potato is one of the most staple food in India, it is in high demand throughout the year and around 80-85% produce of Rabi potato is stored in different cold storages of the major Potato growing states. In terms of market arrival, Potato arrives in Azadpur (Delhi) market (one of the major potato consuming state) from Uttar Pradesh, Punjab, Himachal Pradesh and Haryana. In the present investigation, Volatility Impulse Response Function (VIRF)[15] has been used to see the impacts of a specific shock on the price volatility spillovers of potato among the five major markets i.e. Agra, Delhi, Bengaluru, Mumbai and Ahmedabad. An empirical comparison the multivariate GARCH models namely DCC and BEKK has been carried out.

Data and Methodology

To study the volatility of price of potatoes among different markets, monthly price data set starting from January, 2005 to April, 2021 in five major markets namely Agra, Delhi, Bengaluru, Mumbai and Ahmedabad is considered. The daily return has been calculated for each market using the formulae: $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t and P_{t-1} denote price at time t and t-1 respectively.

MGARCH Model

Multivariate GARCH (MGARCH) models are used commonly to estimate volatility spillovers among different markets. For a multivariate time series, the MGARCH model is given by:

$$y_t = H_t^{1/2}\varepsilon_t$$

where, H_t is $k \times k$ positive-definite matrix of conditional variance. k is the number of series and $t = 1,2,\ldots,n$ *(observations*). It is with the specification of conditional variance that the MGARCH model changes.

BEKK Model

The study makes use of the BEKK model proposed by the Baba, Engle, Kraft and Kroner [16,17]. The BEKK (1,1) model is:

$$H_t = CC' + A \in_{t-1}\in_{t-1}' A' + BH_{t-1}B'$$

Each element of H_t depends on the p delayed values of the squared ε_t, the cross product of ε_t and on the q delayed values of elements from H_t.

The off diagonal parameters in matrix B, b_{12} and b_{21} respectively measures the dependence of conditional price volatility of first market to the second market and vice-versa. The parameters b_{11} and b_{22} represents persistence in volatility in their own market. The parameters a_{12} or a_{21} represent the cross markets effects whereas a_{11}, a_{22} represent the own market effects. Therefore, the significant level of each parameter indicates the presence of strong ARCH or GARCH effect.

Dynamic conditional correlation (DCC) Model

The dynamic nature of time varying correlations has been studied using DCC-GARCH model developed by Engle[2]. The DCC model can be formulated in a following manner:

$$y_t = \mu_t(\theta) + \varepsilon_t$$

where$\varepsilon_t$is a $n \times 1$ vector of zero mean in which innovations conditional on the information available at time *t-1*. The conditional variance co-variance matrix can be written as:

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}}$$

where, R_t is the $n \times n$ conditional correlation matrix and the matrices D_t and R_t are computed as follows:

$$D_t = diag(h_{11t}^{\frac{1}{2}}, \ldots, h_{nnt}^{\frac{1}{2}})$$

h_{iit} is chosen to be a univariate GARCH (1,1) process; $R_t = (diagQ_t)^{-1/2}Q_t(diagQ_t)^{-1/2}$,

$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}$ refers to a $n \times n$ symmetric positive definite matrix with $u_{it} = {\varepsilon_{it}}/{\sqrt{h_{iit}}}$, $\bar{Q}$ is the $n \times n$ unconditional variance matrix of u_t and α and β are non negative scalar parameters satisfying $\alpha + \beta < 1$.

The conditional correlation coefficient ρ_{ij} between two markets i and j is then computed as follows:

$$\rho_{ij} = \frac{(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{i,t-1}u_{j,t-1} + \beta q_{ij,t-1}}{((1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1})^{1/2}((1-\alpha-\beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta q_{jj,t-1})^{1/2}}$$

whereρ_{ij} refers to the element located in the i^{th} row and j^{th} column of the symmetric positive definite matrix Q_t .

Volatility Impulse Response Functions

The volatility impulse response functions (VIRF) describe the impact of an independent shock on the volatility of the variables. The nature of independence of the given shock from other previous shocks allow the construction of VIRF from historical data. However, in a multivariate setup it is hard to assume that shocks are independent if they all occur at the same time. In such cases Cholesky decomposition is used for the orthogonalization of residuals. For the present investigation, the methodology by Hafner and Herwartz has been followed to compute the VIRF[12].

Results and Discussion

The pattern of prices of potato in different markets is displayed in fig.1. It can be visualized that the prices vary a lot over the time period leading to volatility. Results obtained for descriptive statistics are reported in Table 1. A perusal of table 1 reveals that mean monthly price of potatoes is maximum in Bengaluru i.e. INR 1139.58/quintal and minimum in Agra at INR 671.19/quintal. Similarly, maximum price of potatoes was observed in Bengaluru at INR 2480/quintal followed by Delhi. The coefficient variation (CV) as depicted in table 1 indicates that Agra markets has highest variation in price followed by Delhi market. Considering the fact that price of potatoes is highly fluctuating in all the markets with marginal difference in standard deviation values, it can be concluded that all markets are subject to high shocks. The kernel density estimates as depicted in figure 2 clearly indicates significant departure from normality.

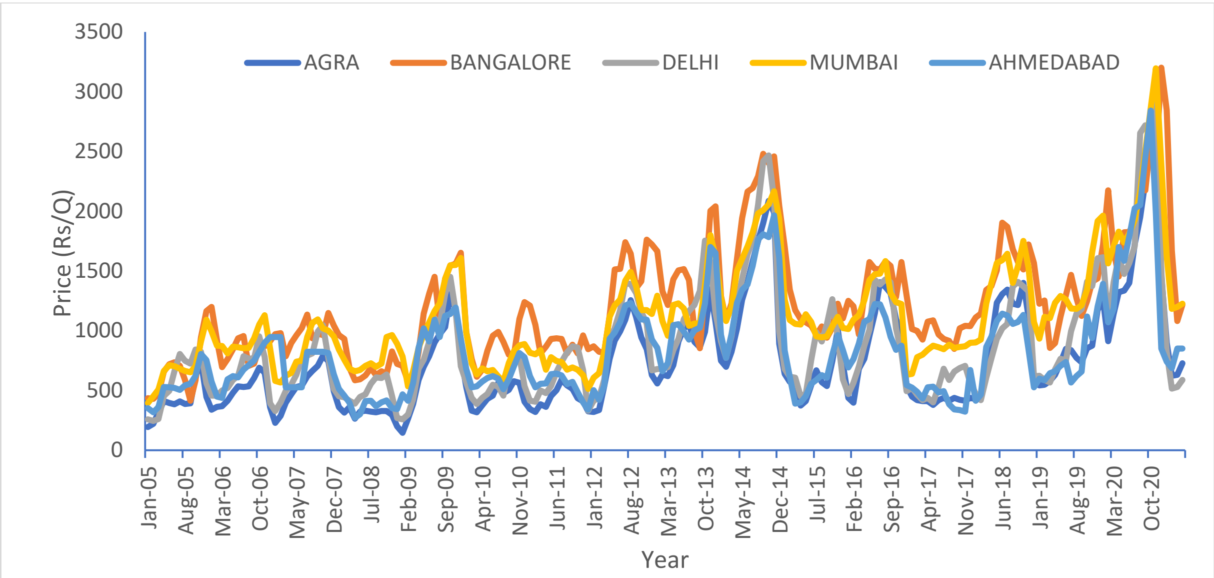


Figure 1. The time plot of potato prices in studied markets

Table 1. Descriptive statistics

Markets	Mean	Median	Maximum	Minimum	Standard Deviation	CV
Agra	671.19	548.00	2086.00	147.00	367.13	54.70
Ahmedabad	763.06	661.00	1965.00	271.00	335.40	43.95
Bengaluru	1139.58	1037.00	2480.00	414.00	417.46	36.63
Delhi	797.75	695.00	2467.00	245.00	399.66	50.10
Mumbai	1029.38	953.00	2167.00	394.00	351.20	34.12

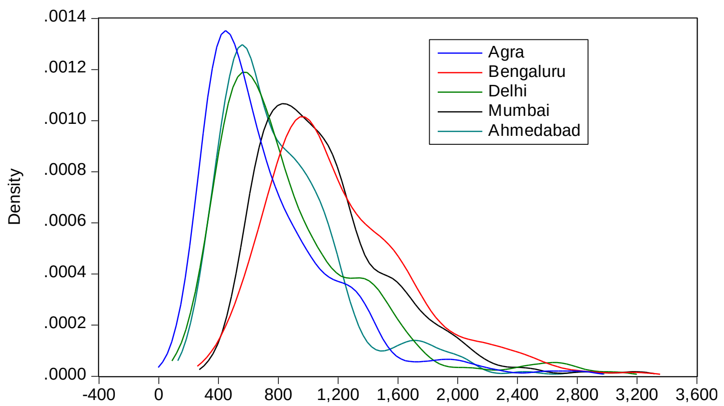


Figure 2. Kernel density function of market price of Potato

The study applied various unit root tests i.e. Augmented Dickey-Fuller (ADF) test and Phillips–Perron (PP) test proposed for checking the stationarity of data. The results of the unit root tests are reported in Table 2. It may be seen that all the log return series are stationary at level.

Table 2. Unit root test results

	ADF test		PP test	
Markets	**t stat**	**p-value**	**t stat**	**p-value**
Agra	-5.04	0.00	-3.85	0.00
Ahmedabad	-4.57	0.00	-3.68	0.01
Bengaluru	-3.40	0.01	-3.06	0.03
Delhi	-5.57	0.00	-4.19	0.00
Mumbai	-4.45	0.00	-3.58	0.01

Table 3. Results of BEKK (1,1) model

	Constant (C)				
	Agra	**Bengaluru**	**Delhi**	**Mumbai**	**Ahmedabad**
Agra	0.157	-0.035	0.151	0.081	0.075
Bengaluru	0.000	0.022	-0.096	0.050	0.061
Delhi	0.000	0.000	0.072	0.031	0.073
Mumbai	0.000	0.000	0.000	-0.014	-0.010
Ahmedabad	0.000	0.000	0.000	0.000	-0.034
	ARCH Coefficients (A)				
	Agra	**Bengaluru**	**Delhi**	**Mumbai**	**Ahmedabad**
Agra	0.218	0.226	0.165	0.279	0.267
Bengaluru	0.047	0.097	-0.276	-0.119	-0.022
Delhi	0.328	0.029	0.134	0.129	-0.216
Mumbai	-0.413	0.230	-0.169	-0.165	-0.198
Ahmedabad	0.094	-0.076	0.251	0.034	0.368
	GARCH Coefficients (B)				
	Agra	**Bengaluru**	**Delhi**	**Mumbai**	**Ahmedabad**

Agra	0.552	-0.254	0.125	-0.261	0.573
Bengaluru	-0.465	-0.810	-0.463	-0.315	-0.712
Delhi	-0.256	0.291	-0.102	0.256	-0.391
Mumbai	0.533	0.404	0.341	-0.086	-0.281
Ahmedabad	0.028	0.347	0.309	0.232	0.304

Standard Error of Coefficient of Constant

	Agra	**Bengaluru**	**Delhi**	**Mumbai**	**Ahmedabad**
Agra	0.028	0.031	0.026	0.015	0.028
Bengaluru	0.000	0.030	0.031	0.018	0.018
Delhi	0.000	0.000	0.038	0.014	0.050
Mumbai	0.000	0.000	0.000	0.012	0.185
Ahmedabad	0.000	0.000	0.000	0.000	0.048

Standard Error of ARCH coefficients

	Agra	**Bengaluru**	**Delhi**	**Mumbai**	**Ahmedabad**
Agra	0.107	0.157	0.212	0.030	0.112
Bengaluru	0.098	0.112	0.134	0.061	0.104
Delhi	0.210	0.127	0.271	0.069	0.115
Mumbai	0.192	0.185	0.237	0.058	0.171
Ahmedabad	0.099	0.073	0.083	0.051	0.091

Standard Error of GARCH coefficients

	Agra	**Bengaluru**	**Delhi**	**Mumbai**	**Ahmedabad**
Agra	0.207	0.261	0.205	0.097	0.327
Bengaluru	0.215	0.107	0.182	0.127	0.206
Delhi	0.295	0.343	0.288	0.136	0.372
Mumbai	0.103	0.254	0.189	0.143	0.650
Ahmedabad	0.206	0.152	0.199	0.082	0.302

The results of the estimated MGARCH- BEKK model for log return series of monthly price of potatoes for five cities namely Agra, Bengaluru, Delhi, Mumbai and Ahmedabad are presented in table 3. In table 3, the ARCH effect of own market and cross markets are represented by matrix A whereas the GARCH effect of own market and cross markets are represented by matrix B.

Table 4 reports the results of DCC model. Here the parameter α measures the reaction of conditional volatility to market shocks and parameter β measures the persistence in conditional volatility irrespective of anything happening in the market. The condition that $0 < \alpha + \beta < 1$ are all satisfied, for all the five markets. The maximum value occurring for Agra at 0.962 and minimum value for Bengaluru at 0.695. In all the markets, value of α is less than β except. The low value of α and high value of β indicates the importance of long-run persistence in comparison to short-run persistence. A close analysis of dcca1 and dccb1 showed that both the coefficients are statistically significant and clearly indicate that system of series as a whole makes sense to fit DCC model.

Table 4. Results of DCC model

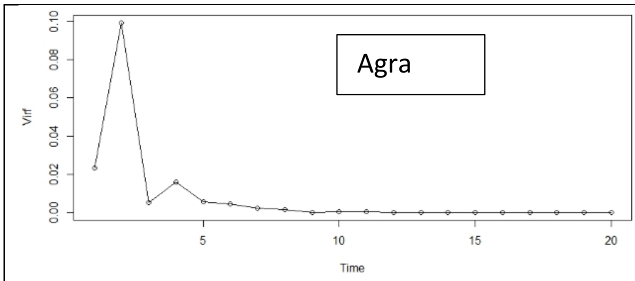
		Agra		
Parameter	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
c	0.007	0.034	0.202	0.840
ω	0.000	0.008	0.007	0.995
α	0.163	0.069	2.354	0.015
β	0.799	0.008	97.450	0.000
		Bengalureu		
c	0.004	0.012	0.354	0.724
ω	0.009	0.005	1.753	0.080
α	0.142	0.064	2.225	0.026
β	0.553	0.211	2.628	0.009
		Delhi		
c	0.005	0.016	0.286	0.775
ω	0.000	0.002	0.049	0.961
α	0.215	0.034	6.288	0.000
β	0.594	0.001	502.113	0.000
		Mumbai		
c	0.006	0.011	0.537	0.591
ω	0.000	0.000	0.063	0.950
α	0.236	0.025	9.489	0.000
β	0.599	0.002	346.643	0.000

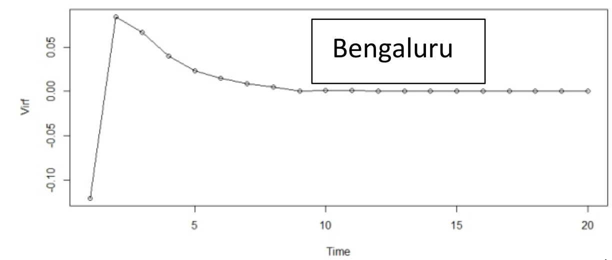
		Ahmedabad		
c	0.005	0.014	0.352	0.725
ω	0.000	0.001	0.146	0.883
α	0.149	0.019	7.995	0.000
β	0.758	0.001	615.584	0.000
dcca1	0.042	0.017	2.494	0.013
dccb1	0.753	0.120	6.257	0.000

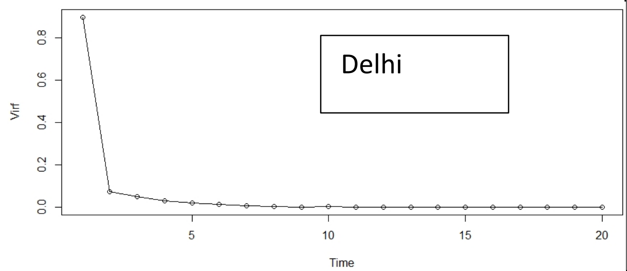
Note: c, ω, α and β denotes respectively the constant in mean equation, constant in variance, ARCH effect and GARCH effect.

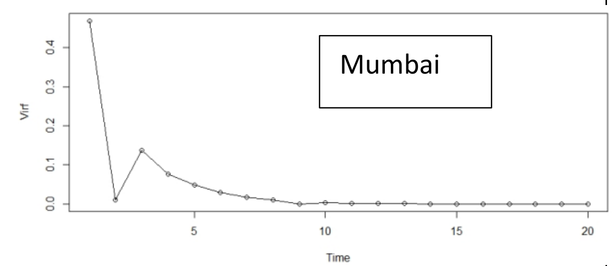
The VIRF depends on the initial volatility H_t given to the system. The value of initial volatility can be either the volatility state at the time of the shock incurred, or any other date chosen from the sample period. Figure 3 shows the volatility impulse responses. The impact of the shock appears not only in the expected conditional variances but also evident in the expected conditional covariances. The impact of the shock on expected conditional variances in all the cities can be evaluated from first month itself.

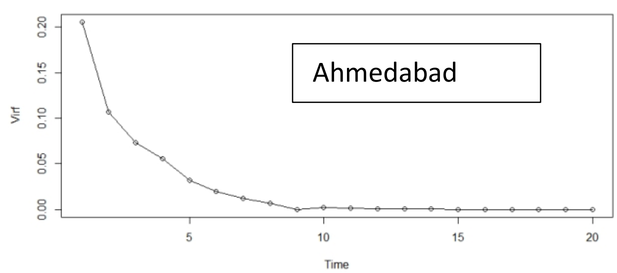
The initial impact of the shock on expected conditional covariances between all the cities was noticeable at point of initial shock and the peak response was reached in about second or third month. Regarding the die down of the impact of the shock on expected conditional covariances, it can be seen that impact of shock didn't sustain after ten months in all the cities. The continuous fluctuations in initial months confirms the fact that volatility transmission across markets is usually attributed to news and cross-market hedging which dynamically changes expectations across markets. A key result to be noted is that even if impact of shock is negative initially for some markets, in terms of both variances and covariances, but duration was very short.

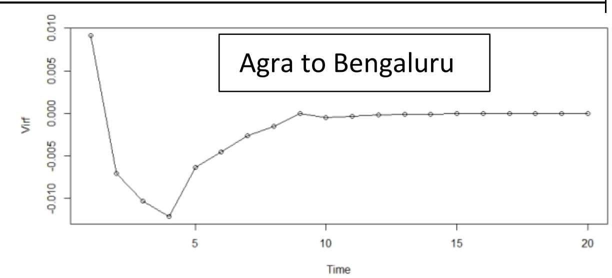

Agra
Virf
0.00 0.02 0.04 0.06 0.08 0.10
5 10 15 20
Time

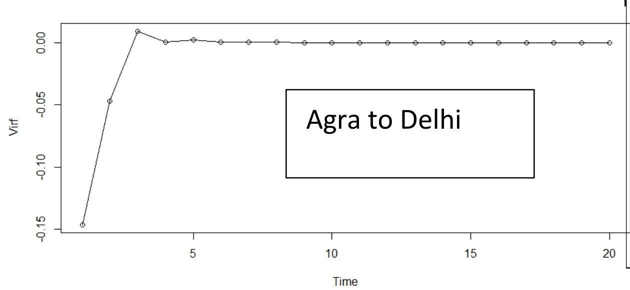

Bengaluru
Virf
-0.10 -0.05 0.00 0.05
5 10 15 20
Time

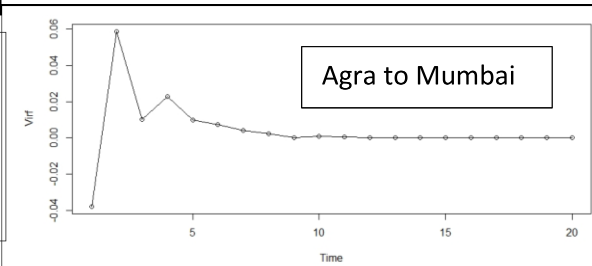

Delhi
Virf
0.0 0.2 0.4 0.6 0.8
5 10 15 20
Time


Mumbai
Virf
0.0 0.1 0.2 0.3 0.4
5 10 15 20
Time


Ahmedabad
Virf
0.00 0.05 0.10 0.15 0.20
5 10 15 20
Time


Agra to Bengaluru
Virf
-0.010 -0.005 0.000 0.005 0.010
5 10 15 20
Time


Agra to Delhi
Virf
-0.15 -0.10 -0.05 0.00
5 10 15 20
Time


Agra to Mumbai
Virf
-0.04 -0.02 0.00 0.02 0.04 0.06
5 10 15 20
Time

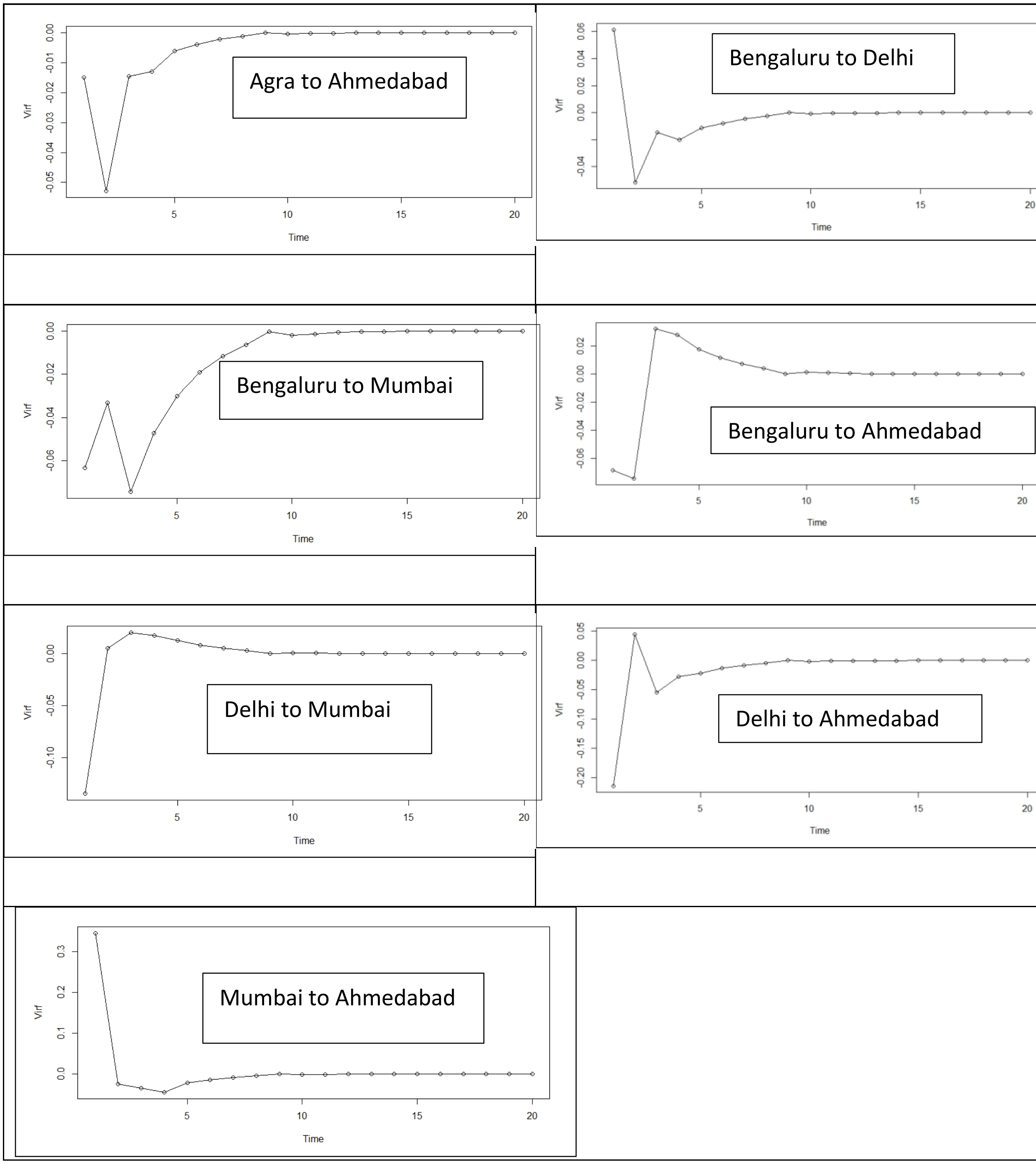


Figure 3. VIRF of different markets

Conclusions

The present study investigated the effect of volatility spillovers in monthly potato price of five different markets Agra, Ahmedabad, Bengaluru, Delhi, and Mumbai from January, 2005 to April, 2021. The empirical results support the presence of ARCH and GARCH effects in all the markets.

Accordingly, to accommodate the conditional heteroscedasticity as well as inter dependence of studied markets, MGARCH models namely BEKK and DCC have been applied. It is observed that price volatility is not only dependent on its own market's past volatility but also depends on cross market volatility. Finally, the application of VIRF demonstrated volatility spillover of all the studied markets and it also showed the impacts of impulse responses on expected conditional variances and expected conditional covariances. To this end one can conclude that changes in the volatility of one market will often trigger reactions in other markets.

References

1. Bellemare, M. F., Barrett, C. B., and Just, D. R., The welfare impacts of commodity price volatility: evidence from rural Ethiopia. *American Journal of Agricultural Economics*, 2013, **95**, 877–899.

2. Engle, R. F., Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 1982, 987–1007.

3. Newbery, D. M., The theory of food price stabilisation. *The Economic Journal*, 1989, **99**, 1065–1082.

4. Zheng, Y., Kinnucan, H. W., and Thompson, H., News and volatility of food prices. *Applied Economics*, 2008, **40**, 1629–1635.

5. Apergis, N. and Rezitis, A., Food price volatility and macroeconomic factors: Evidence from GARCH and GARCH-X estimates. *Journal of Agricultural and Applied Economics*, 2011, **43**, 95–110.

6. Candila, V. and Farace, S., On the volatility spillover between agricultural commodities and Latin American stock markets. *Risks*, 2018, **6**, 116.

7. Paul, R. K., Prajeshnu and Himadri, G., GARCH nonlinear time series analysis for modelling and forecasting of India's volatile spices export data. *Journal of the Indian Society of Agricultural Statistics*, 2009, **63**, 123–131.

8. Paul, R. K., Saxena, R., Chaurasia, S., and Rana, S., Examining export volatility, structural breaks in price volatility and linkages between domestic and export prices of onion in India. *Agricultural Economics Research Review*, 2015, **28**, 101–116.

9. Paul, R. K., Bhardwaj, S. P., Singh, D. R., Kumar, A., Arya, P., and Singh, K. N., Price Volatility in Food Commodities in India-An Empirical Investigation. 2015.

10. Paul, R. K., Rana, S., and Saxena, R., Effectiveness of price forecasting techniques for capturing asymmetric volatility for onion in selected markets of Delhi. *The Indian Journal of Agricultural Sciences*, 2016, **86**.

11. Singla, S., Paul, R. K., and Shekhar, S., Modelling price volatility in onion using wavelet based hybrid models. *Indian Journal of Economics and Development*, 2021, **17**, 256–265.

12. Hafner, C. and Herwartz, H., *Time-varying market price of risk in the CAPM* Humboldt-Universität zu Berlin, Wirtschaftswissenschaftliche Fakultät, 1999.

13. Sinha, K., Gurung, B., Paul, R. K., et al., Volatility spillover using multivariate GARCH model: an application in futures and spot market price of black pepper. 2017.

14. Paul, R. K., Das, T., Panwar, S., Paul, A. K., and Bhar, L. M., Volatility and spillover in onion prices in major markets of Karnataka, India. *Indian Journal of Agricultural Marketing*, 2019, **33**, 65–76.

15. Koop, G., Pesaran, M. H., and Potter, S. M., Impulse response analysis in nonlinear multivariate models. *J Econom*, 1996, **74**, 119–147.

16. Baba, Y., Engle, R. F., Kraft, D. F., and Kroner, K. F., Multivariate simultaneous generalized ARCH. *Manuscript*, *University of California*, *San Diego*, *Department of Economics*, 1990.

17. Engle, R. F. and Kroner, K. F., Multivariate simultaneous generalized ARCH. *Econ Theory*, 1995, **11**, 122–150.