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PRICE VOLATILITY SPILLOVER IN DOMESTIC COTTON MARKETS OF PAKISTAN: AN APPLICATION OF DCC-MGARCH MODEL*

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ABSTRACT

The identification of interdependencies among various product markets is imperative both from the macro and microeconomic viewpoint. This paper examines price volatility spillover effects among ten domestic cotton markets (7 from Punjab and 3 from Sindh) of Pakistan by employing the DCC-MGARCH model. Analysis is done using quarterly wholesale prices of seed cotton from 1st quarter of the year 1991 till second quarter of 2017. Results indicate that seed cotton prices are volatile in all the domestic markets considered as well as volatility is persistent. Dynamic conditional correlation coefficient shows that seed cotton markets have positive conditional correlation with each other. It is concluded from the study results that because of volatile nature of cotton prices, farmer's profit is at risk. This further suggests the government's investment in road and infrastructure and intervention in seed cotton markets to keep the markets stable and support cotton farmers against risk.

Keywords: Cotton, price volatility spillover, volatility clustering, volatility persistance, DCC-MGARCH

Jel Classification: C22 ,C32 ,Q11 ,Q13.

INTRODUCTION

Cotton, known as "white gold" of Pakistan, is one of the most traded agricultural commodities of the world. Grown on country's 15 percent arable land, cotton is Pakistan's main industrial crop. It is raised during the summer season from May to August and there is also a small spring crop cultivated from February to April. Punjab is the largest producer of cotton in Pakistan with 75% share in country's cotton production followed by Sindh which contributes about 25% (Rehman, 2015). Cotton is important not only for its fiber but it is a big source of raw material for food (cooking oil) and feed industries. For the countries like Pakistan its sticks are also used as fuel. Cotton crop has 1% share in GDP and contributes 5.2 % in agriculture value addition (GOP, 2016). About Sixty percent of the export earnings of Pakistan come from the cotton and textile sector (Khan *et. al.*, 2011). That's why the economy of Pakistan is greatly dependent on the cotton-yarn-textile- apparel complex (Altaf, 2008). The integrated cotton and textile sector comprises of 1,000 ginneries, 425 textile mills, and 300 cottonseed crushers and oil refineries (Rehman, 2015).

Marketing channel of seed cotton in Pakistan involves cotton producers, ginners, textile mills and middlemen at various steps of marketing. Middlemen are known as beopari (Buys at farm gate and bears all the cost to bring the output to the wholesale market), arhti (sale seed cotton to the ginners), and brokers (Ginners sale cotton lint to textile mills through brokers) (Manan *et. al.*, 2013). Marketing chain of seed cotton is elaborated in figure 1. Government provides price support to cotton producers through input subsidies as well as the crop procurement program. Crop procurement price sets a floor price for the crop to ensure that cotton producers may get reasonable profit.

In a decentralized economic system resource allocation takes place through the price signals transmitted by the market (Hussain *et al.*, 2010). Prices of agricultural commodities including cotton are intrinsically unstable (Haile, *et. al.* 2013). Dramatic changes in both the mean and variance of international agricultural prices have been observed during recent years (Gilbert, 2010; Cabrera and Schulz, 2016). The price index of agricultural raw materials rose steadily from 139 in March 2009 to 212 in September 2010 on the back of strong world demand (U.N.,2011).Cotton prices have also been fluctuating a lot. Cotton prices reached historic peaks as a significant drop in world cotton production recorded in 2009-10, while demand for fibers from Asian emerging economies increased sharply (U.N.,2011).

Price variations are not problematic if they represent smooth trend of market fundamentals (UNCTAD, 2011). However, unanticipated, large and prolonged variations become challenging as they create risk and uncertainty for market stakeholders including producers, traders, consumers and governments (Kroner *et al.*, 1995). During the spell of adversities, volatility could be self-leading which causes market agents to represent a "herd-like" behavior as they follow the price trends while making decisions instead of following market fundamentals (Rapsomanikis, 2011). The main reason of unstable agricultural commodity prices are social economic, and geopolitical events which strongly affect agriculture commodity prices, whereas, consumers, producers and governments seem to be not capable enough to cope with the consequences of highly volatile agricultural prices.

The identification of interdependencies among various product markets is imperative both from the macro and microeconomic viewpoint as volatile agricultural prices affect the forces of supply, demand as well as market equilibrium. The efficiency of the farm sector depends not only on farm production costs and yields, but also on marketing opportunities and the rate of return to the farmers (UNCTAD, 2011). Price variability is a significant element of profit capriciousness as well. The information on the relationship of product price variability in various markets is important for private investment decisions in farming and farm product marketing (Heifner and Kinoshita, 1994). Furthermore, the producer's wellbeing depends on the prices they receive for their product and consumer's income is affected via prices they pay for agricultural commodities (Sexton *et al*., 1991). Therefore it is very important to quantify price variability of agricultural products.

As cotton has a significant share in total national agricultural output and exports of Pakistan, study on cotton price volatility and its spread among various domestic markets is indispensable. Precise estimation of the stochastic component of agricultural prices aids the decision maker in making wise choices about the crops to consider in any cultivation season. It also contributes to policy decisions concerning the possible implementation of commodity price stabilization or crop procurement programs (Jordaan *et. al*., 2007). Besides, agricultural commodity price volatility is still an area in which little empirical attention has been paid. Particularly, cotton market watch for a developing economy like Pakistan is a must. There are several foreign studies which focused on agricultural price variability and volatility spillover (Du and McPhail , 2012; Gilbert and Mugera , 2014; Saucedo *et. al*., 2015; Etienne, *et. al*., 2017; Müller, 2017; Adämmer *et. al*., 2017) . However, literature focusing on crop price volatilities in Pakistan is lacking. Earlier studies related to cotton market prices in Pakistan focused on the market integration at mean price level (Tahir, 1997; Mushtaq et. al., 2007). However, cotton price variability is an issue that has not been investigated yet. With this background, the aim of the present study is to analyze the cotton price dynamics among selected cotton markets of Pakistan. The specific objective is to explore the answer for the questions that whether cotton prices in various markets are volatile? If yes whether volatilities among various domestic cotton markets are correlated?

MATERIALS AND METHODS

i- **Data:** Quarterly wholesale prices of cotton ranging from 1st quarter of the year 1991 till second quarter of 2017 were used for the price volatility transmission analysis among various domestic markets of Pakistan (Figure. 2). Wholesale price data for ten markets including seven markets from Punjab province and three markets from Sindh province in Pakistan are collected from various sources including Economic survey of Pakistan (GOP, 1995; 1999; 2016), Agricultural statistics of Pakistan (GOP, 2000; 2005; 2013) and Pakistan Central Cotton Committee's market reports. For the purpose of the present study logarithmic returns of the wholesale price series were calculated using the following mathematical relationship:

$$r_t = 100(\ln (P_t) - \ln (P_{t-1})) \quad (1)$$

Where, rt = log returns of the prices under consideration, P_t = Whole sale price in time t, P_{t-1} = Whole sale price in time t-1.

Price return series for the ten selected seed cotton markets are represented as **rtryk** (Rahim Yar Khan), **rtbwp** (Bahawalpur), **rtbur** (Burewala), **rtmtn** (Multan), **rtshw** (Sahiwal), **rtokr** (Okara), **rtfsd** (Faisalabad), **rthyd** (Hyderabad), **rtnwbsh** (Nawabshah), and **rtsgr** (Sanghar). (For graphical depiction of return series see figure. 3a, 3b)

ii- **ARCH-GARCH Modeling : Basic Idea**

ARCH models have potential of modeling and capturing many of the stylized facts of the volatility behavior usually observed in financial time series including time varying volatility or volatility clustering (Zivot and Wang, 2006). Simple AR process for the squared residuals can be used to model the serial correlation in squared returns, or conditional heteroscedasticity (volatility clustering). Consider y_t as a stationary time series such as log-returns of cotton prices. y_t can be represented as its mean plus a white noise if there is no significant autocorrelation in y_t itself;

$$y_t = c + \mu_t \quad (2)$$

Where, c is the mean of y_t and μ_t is a white noised error term μ_{t-1}^2. In order to model volatility assume that Var_{t-1} () = σ_t^2 where, $\mathrm{Var}_{t-1}(.)$ is the conditional variance

$$\sigma_t^2 = \alpha_0 + \alpha_1\mu_{t-1}^2 + \cdots + \alpha_P\mu_{t-P}^2 \quad (3)$$

A more parsimonious model proposed by (Bollerslev, 1986) replaces the AR model in equation 3 with the following formulation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{P}\alpha_i\varepsilon_{t-1}^2 + \sum_{j=1}^{q}\beta_j\,\sigma_{t-j}^2 \quad (4)$$

Where to ensure the positive variance, all the coefficients of α_i and β_j are assumed to be positive. Equation 1 and 4 together form a generalized GARCH (p, q) model. When q = 0, the GARCH model reduces to the

ARCH model. A typical GARCH (1, 1) can be written as follows:

$$\sigma_{t1}^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (5)$$

Where σ_t^2 is the conditional variance from the conditional mean equation, ε_t^2 is the squared error term from the equation for conditional mean, *i* indexes markets and t indexes time periods.

iii- **Modeling Cotton Price Volatility in Domestic Markets of Pakistan:** Modeling volatility of price return series is considered as a measure of risk because return series generally exhibit several stylized facts including volatility clustering, fat tail, skewness and high kurtosis. The simplest way to model volatility is by assuming constant conditional correlation as in CCC-GARCH model proposed by Bollerslev (1990). However, assuming constant conditional correlations over time is too restrictive supposition. Engle (2002), Tse and Tsui (2002) proposed a generalization of Bollerslev's (1990) model by assuming time varying conditional correlation matrix.

According to Engle and Sheppard (2001), analyzing and understanding how the univariate GARCH works is fundamental for the study of the Dynamic Conditional Correlation multivariate GARCH model. The DCC model is a nonlinear combination of univariate GARCH and its matrix is based on how the univariate GARCH (1, 1) process works (Nortey *et al*., 2015). DCC-MGARCH models enable to analyze interdependence among markets by estimating the time-varying conditional correlation (Engle, 2002). Bivariate DCC-MGARCH model in a variety of situations is often more accurate as compared to several other estimators and provides practically logical results (Engle, 2002). So, in our study, in order to capture the time varying volatility (conditional heteroscedasticity) in cotton market prices, we used bivariate DCC-MGARCH model. Specifically, we utilized DCC-MGARCH (1, 1) model based on Akaike Information Criteria (AIC). The specified mean equation in the DCC-MGARCH (1, 1) model for a given pair of domestic cotton markets of Pakistan can be written as:

$$Y_{it} = \gamma_0 + \sum_{k=1}^{p}\gamma_{1k}Y_{it-k} + \sum_{k=1}^{p}\gamma_{2k}Y_{jt-k} + \gamma_3 B_t + \mu_{i,t} \quad (6)$$

$$Y_{jt} = \delta_0 + \sum_{k=1}^{p}\delta_{1k}Y_{jt-k} + \sum_{k=1}^{p}\delta_{2k}Y_{it-k} + \delta_3 B_t + \mu_{j,t} \quad (7)$$

$$\sigma_{i,t}^2 = \gamma_{10} + \alpha_{11}\mu_{i,t-1}^2 + \beta_{11}\sigma_{i,t-1}^2 \quad (8)$$

$$\sigma_{j,t}^2 = \gamma_{20} + \alpha_{21}\mu_{j,t-1}^2 + \beta_{21}\sigma_{j,t-1}^2 \quad (9)$$

Where, Y_{it} is price returns in market i, Y_{jt} is price returns in market j. B_t is the dummy variable to take into account the historic cotton price boom during 2009-11, which assumes a value equal to one during first quarter of 2009 till first quarter of 2011 and zero otherwise. γ_{10} and γ_{20} are constants and show "ambient volatility". α shows adjustment to previous shocks whereas, *β* shows adjustment to previous volatility (Got *et al* 2013; Bloznelis, 2016). Error term (μ_t) has the following conditional variance-covariance matrix:

$$H = D_t R_t D_t \quad (10)$$

Where D_t is a diagonal n x n (n=2 for our case) matrix of conditional variances (σ_{nt}^2) in which each σ_{nt}^2 is generated according to the GARCH model represented in equations 6 through 9.

R_t is a n x n symmetric correlation matrix that is defined as follows

$$R_t = (diag(Q_t))^{-1/2}\bar{Q}_t\,(diag(Q_t))^{-1/2} \quad (11)$$

Where,

$$Q_t = \{q_{ij,t}\} = (1 - \alpha - \beta)\bar{Q}_t + \beta Q_{t-1} + \alpha(\mu_{t-1}, \mu_{t-1})$$

Where, $\alpha + \beta > 1$, α < 1, β < 1. If the restriction $\alpha + \beta < 1$ is violated and $\alpha + \beta = 1$then, GARCH model has unit root and it becomes integrated GARCH (IGARCH). If sum of *α* and *β* is greater than 1, that means the series is explosive and doesn't revert back to its equilibrium. DCC-MGARCH model mainly focuses on finding conditional correlations in R_t represented as follows;

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} \quad (12)$$

iv- **Model Estimation:** Procedural steps involved in estimating the GARCH model are presented in figure. 4. Descriptive statistics of the each price return series is analyzed using the indicators including mean, median and mode. Skewness, kurtosis and Jarque-Berra statistics is applied to test the data distribution. Before, proceeding to the estimation of GARCH model, each return series is tested for stationarity using Augmented Dickey Fuller test (Dickey and Fuller, 1981). Residuals of each return series are also tested for the presence of ARCH effect so as to decide, whether the ARCH/GARCH model specification is suitable or not. In an AR (ρ) model:

$$y_t = \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \cdots + \gamma_n y_{t-\rho} + \varepsilon_t \quad (13)$$

The testing of ARCH effects basically involves the following regression:

$$\hat{\varepsilon}_t^2 = a_1\hat{\varepsilon}_{t-1}^2 + a_2\hat{\varepsilon}_{t-2}^2 + \cdots + a_\rho\hat{\varepsilon}_{t-\rho}^2 + \varphi_t \quad (14)$$

The null hypothesis that there is no ARCH effects up to p lags i.e.

$$H_0 = a_1 = a_2 = \cdots = a_p = 0$$

The alternative hypothesis is that the errors are ARCH (ρ). The Lagrange Multiplier test statistic is;

$$LM = T.R^2 \sim \chi_{(p)}^2 \quad (15)$$

Where, T represents number of observations. Rejection of null hypothesis ensures the presence of ARCH effects in the price data.

The specified DCC- MGARCH model for each market pair is estimated using maximum likelihood method assuming the independently and identically distributed standardized residuals.

RESULTS AND DISCUSSION

Descriptive statistics for the nominal cotton price return series in various cotton markets used in the analysis show several stylized facts (Table 1). The Jarque-Bera test indicates that all the price returns series do not follow a normal distribution. The kurtosis in all of the analyzed markets is greater than 3, further pointing to a leptokurtic distribution of returns. Hence return series exhibit a positively skewed, relatively peaked and fat tailed distribution. Application of GARCH models requires that data series should be stationary at levels. Presence of unit root was tested in all the price returns using ADF test (Table 2). Results show that the test statistic is statistically highly significant which leads to the conclusion of absence of unit root in all the return series. Therefore, log returns of price series are utilized for the volatility spillover analysis. By applying the ARCH-LM test of Engle (1982), we strongly reject the null hypothesis of no ARCH effects at the conventional levels of price return series in all cases. Thus, we find that the use of a GARCH-based approach particularly DCC-MGARCH (1, 1) is appropriate for modelling stylized facts such as fat-tails, volatility clustering, and persistence in cotton price returns.

A bivariate DCC- MGARCH (1, 1) model was estimated for all the possible pairs of the selected seed cotton markets of Pakistan. Statistically significant dummy variable in all the mean returns equation shows that in the time of price crises i.e. during 2009-11 cotton markets were integrated, highly volatile and were transmitting abrupt price fluctuations to each other. Table 3 represents the results for ARCH (α) and GARCH (β) parameters for the market pairs for which convergence is achieved. ARCH parameter represents whether the return series show the volatility clustering while the GARCH parameter represents whether the volatility in particular series is persistent or not. Sum of ARCH and GARCH parameters is known as persistence parameter (ƛ) which is utilized to calculate half-life. Half-life is the time required for the current mean of the price return series to arrive back half of the way towards its long run conditional mean after a shock (Khan, 2006).

Results of DCC-MGARCH model show that all the price series exhibit the volatility clustering and that volatility is persistent as well. The ARCH coefficients (α) in all the market pairs are positive and statistically significant. This means that cotton price return series in domestic seed cotton markets are volatile. Magnitude of ARCH parameter ranges between 0.14 (for Hyderabad in Hyderabad -Sahiwal markets pair) and 0.75 (for Multan in Multan-Sahiwal pair) while, average value for the ARCH parameter is 0.29.

The GARCH coefficients (β) are also statistically significant in all the market pairs which is indicative of autoregressive memory in the conditional variance. Value of GARCH parameter ranges from 0.11 (for Multan in Multan-Sahiwal markets pair) to 0.69 (for Burewala in Burewala-Sahiwal markets pair), with average value of parameter being 0.45.

GARCH volatilities with relatively high α and low β are spikier compared to those with relatively low α and high β (Alexaneder, 2008). Results show that Hyderabad, Rahim Yar Khan, Okara, Multan and Sahiwal markets are more volatile and riskier as compared to other markets. Estimated half-life for all the return series ranges between 0.8 (for Bahawalpur and Faisalabad) and 9.6 (For Rahim Yar Khan). Average estimated half-life for all the price returns is 3.08, that is, after a shock it takes about 3 periods (approximately 9 months) for a series to fill the half of the gap between its present value and its long run equilibrium.

DCC parameter shows the dynamic conditional correlation between the errors of two return series (Table 4). Results show that all the markets within Punjab have very high dynamic conditional correlation with each other with the magnitude closer to 1. Markets located within Sindh province also have positive dynamic conditional correlation with each other. Nawabshah and Sanghar markets don't have dynamic conditional correlation with the markets located in Punjab. However, Hyderabad market does have a positive conditional correlation with all the markets in Punjab. This means that markets are integrated as well as they transmit price fluctuations to each other making seed cotton markets riskier.

Table 1 Descriptive statistics of quarterly return price series

	RTBUR	RTBWP	RTFSD	RTHYD	RTMTN	RTNWBSH	RTOKR	RTRYK	RTSGR	RTSHW
Mean	2.2213	2.1886	2.1513	2.1355	2.1786	2.1457	2.1636	2.1811	2.1400	2.1439
Median	0.6857	0.7790	0.7490	0.5309	0.6912	0.7528	0.6872	0.6033	1.3008	0.6042
Maximum	119.927	121.1434	122.6295	98.19410	122.4175	120.9995	123.5323	119.6446	119.9697	120.2639
Minimum	-91.936	-92.084	-93.096	-73.188	-92.802	-91.562	-94.038	-91.779	-91.201	-93.686
Std. Dev.	20.000	20.0457	20.4045	18.8995	20.1962	19.3140	20.4829	20.1424	19.7820	20.5849
Skewness	1.0609	1.0841	1.0846	0.7993	1.1566	1.1533	1.1622	1.0192	1.0282	1.0253
Kurtosis	17.387	17.696	17.304	10.510	17.948	20.010	17.776	16.852	17.791	16.227
Jarque-	925.268	965.5686	915.7431	257.9728	1000.988	1289.201	978.9321	857.7006	975.7404	783.9205

Bera										
ARCH-LM	7.716	8.143	7.938	8.528	9.217	8.685	7.717	12.319	7.681	11.599
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observation	105	105	105	105	105	105	105	105	105	105

Table 2 ADF-Test on return series

Province	**District**	**Variable**	**Level without trend**
SINDH	Hyderabad	RTHYD	-14.44018^{***}
	Nawabshah	RTNWBSH	-14.59936^{***}
	Sanghar	RTSGR	-14.63824^{***}
PUNJAB	Bahawalpur	RTBWP	-14.55358^{***}
	Okara	RTOKR	-14.91402^{***}
	Burewala	RTBUR	-9.934747^{***}
	Multan	RTMTN	-14.62357^{***}
	Sahiwal	RTSHW	-14.3565^{***}
	Rahim Yar Khan	RTRYK	-14.44328^{***}
	Faisalabad	RTFSD	-14.53856^{***}

Table 3 Pairwise DCC-MGARCH model results

Market pairs	**ARCH (α)**	**GARCH (β)**	**$\lambda = \alpha + \beta$**	**Half-life = ln (0.5) / ln (λ)**
RTHYD	0.39^{**}	0.40^{***}	0.79	2.9
RTNWBSH	0.43^{**}	0.33^{***}	0.76	2.5
RTHYD	0.28^{*}	0.65^{***}	0.93	9.6
RTSGR	0.32^{***}	0.54^{***}	0.86	4.6
RTHYD	0.22^{*}	0.62^{***}	0.84	3.9
RTBWP	0.31^{*}	0.38^{***}	0.69	1.9
RTHYD	0.32^{**}	0.57^{***}	0.89	5.9
RTOKR	0.34^{***}	0.44^{***}	0.78	2.8
RTHYD	0.26^{**}	0.63^{***}	0.89	5.9
RTBUR	0.32^{**}	0.44^{***}	0.76	2.5
RTHYD	0.25^{**}	0.64^{***}	0.89	5.9
RTMTN	0.31^{**}	0.43^{***}	0.74	2.3
RTHYD	0.14^{***}	0.67^{***}	0.81	3.3
RTSHW	0.19^{***}	0.46^{***}	0.65	1.6
RTHYD	0.48^{**}	0.32^{**}	0.80	3.1
RTRYK	0.49^{**}	0.31^{**}	0.80	3.1
RTHYD	0.21^{**}	0.62^{**}	0.83	3.7
RTFSD	0.28^{***}	0.39^{***}	0.67	1.7
RTNWBSH	0.41^{**}	0.39^{**}	0.80	3.1
RTSGR	0.42^{**}	0.40^{**}	0.82	3.5
To be continued				
RTBWP	0.16^{**}	0.26^{*}	0.42	0.8
RTOKR	0.18^{**}	0.52^{**}	0.70	1.9
RTBWP	0.29^{**}	0.44^{***}	0.73	2.2
RTBUR	0.32^{**}	0.42^{**}	0.74	2.3
RTBWP	0.21^{***}	0.62^{***}	0.83	3.7
RTMTN	0.23^{***}	0.60^{***}	0.83	3.7
RTBWP	0.18^{***}	0.30^{***}	0.48	0.9
RTSHW	0.21^{***}	0.31^{***}	0.52	1.1
RTBWP	0.49^{***}	0.35^{**}	0.84	3.9
RTRYK	0.51^{***}	0.32^{**}	0.83	3.7
RTBWP	0.21^{***}	0.58^{**}	0.79	2.9
RTFSD	0.23^{***}	0.62^{**}	0.85	4.3

RTOKR	0.22***	0.55**	0.77	2.7
RTBUR	0.25***	0.50***	0.75	2.4
RTOKR	0.29***	0.57***	0.86	4.6
RTMTN	0.32***	0.54***	0.86	4.6
RTOKR	0.28***	0.41**	0.69	1.9
RTSHW	0.27***	0.29***	0.56	1.2
RTOKR	0.45***	0.25***	0.70	1.9
RTRYK	0.47***	0.21***	0.68	1.8
RTOKR	0.18**	0.28***	0.46	0.9
RTFSD	0.19**	0.23***	0.42	0.8
RTBUR	0.31***	0.45***	0.76	2.5
RTMTN	0.30***	0.44***	0.74	2.3
RTBUR	0.22***	0.61***	0.83	3.7
RTSHW	0.20***	0.69**	0.89	5.9
RTBUR RTRYK	0.19***	0.63***	0.82	3.5
	0.19***	0.59***	0.78	2.8
RTBUR	0.19***	0.63***	0.82	3.5
RTFSD	0.29***	0.60***	0.89	5.9
RTMTN	0.75***	0.11***	0.86	4.6
RTSHW	0.73***	0.12***	0.85	4.2
RTMTN RTRYK	0.19***	0.47***	0.66	1.7
	0.21***	0.43***	0.64	1.6
RTMTN	0.22***	0.49**	0.71	2.0
RTFSD	0.21***	0.52***	0.73	2.2
RTSHW	0.28***	0.51*	0.79	2.9
RTRYK	0.27***	0.55**	0.82	3.5
RTSHW	0.24***	0.44***	0.68	1.8
RTFSD	0.23***	0.49***	0.72	2.1

Table 4 Dynamic conditional correlations of errors of return series

	RTHYD	**RTNWBSH**	**RTSGR**	**RTBWP**	**RTOKR**	**RTBUR**	**RTMTN**	**RTSHW**	**RTRYK**	**RTFSD**
RTHYD	-									
RTNWBSH	0.90***	-								
RTSGR	0.89***	0.99***	-							
RTBWP	0.64***	Convergence not achieved	Converg-ence not achieved	-						
RTOKR	0.42*	Convergence not achieved	Converg-ence not achieved	0.99***	-					
RTBUR	0.80***	Convergence not achieved	Converg-ence not achieved	0.99***	0.99***	-				
RTMTN	.55***	Convergence not achieved	Converg-ence not achieved	0.99**	0.99***	0.99***	-			
RTSHW	0.82***	Convergence not achieved	Converg-ence not achieved	0.99**	0.99***	0.99***	0.99***	-		
RTRYK	0.66**	Convergence not achieved	Converg-ence not achieved	0.99***	0.99***	0.99***	0.99***	0.99***	-	
RTFSD	.66***	Convergence not achieved	Converg-ence not achieved	0.99**	0.99***	0.99***	0.99***	0.99***	0.99***	-

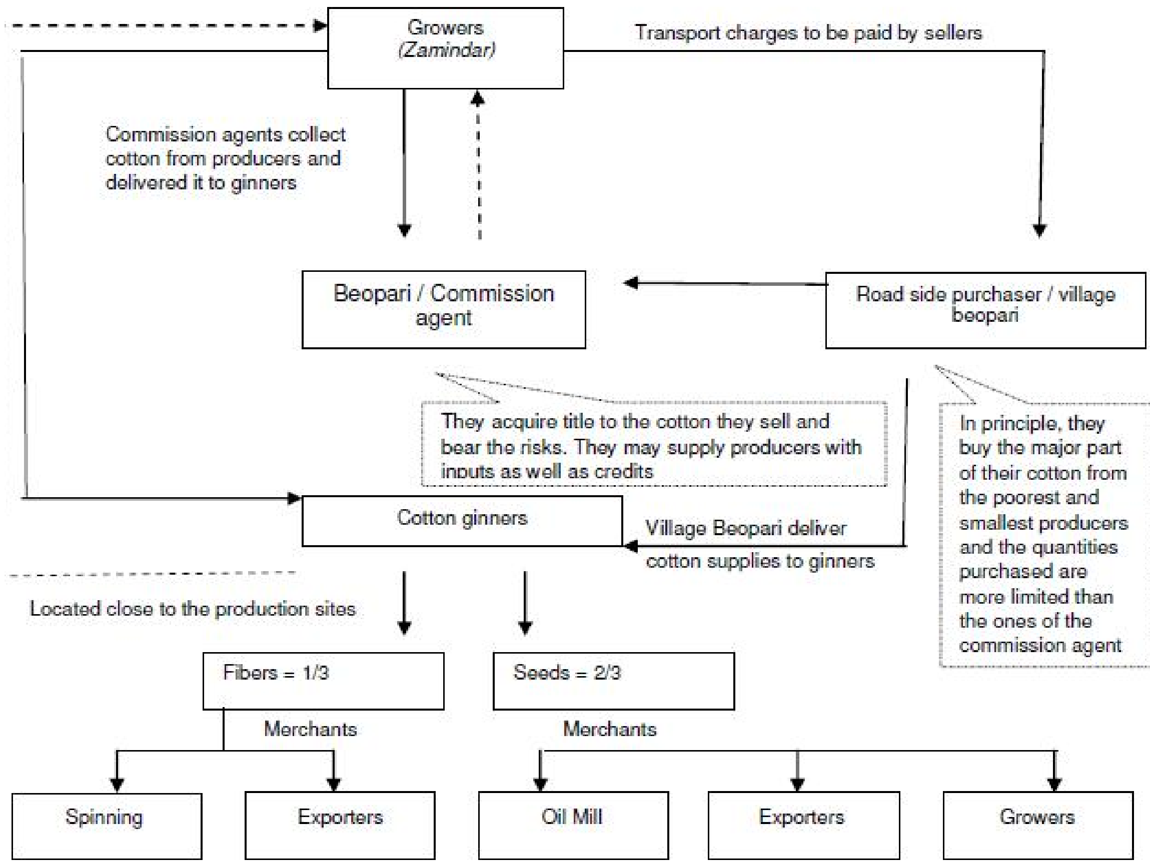

Figure 1 Marketing Channel of Cotton in Pakistan
Source: Khan et. al, (2011)

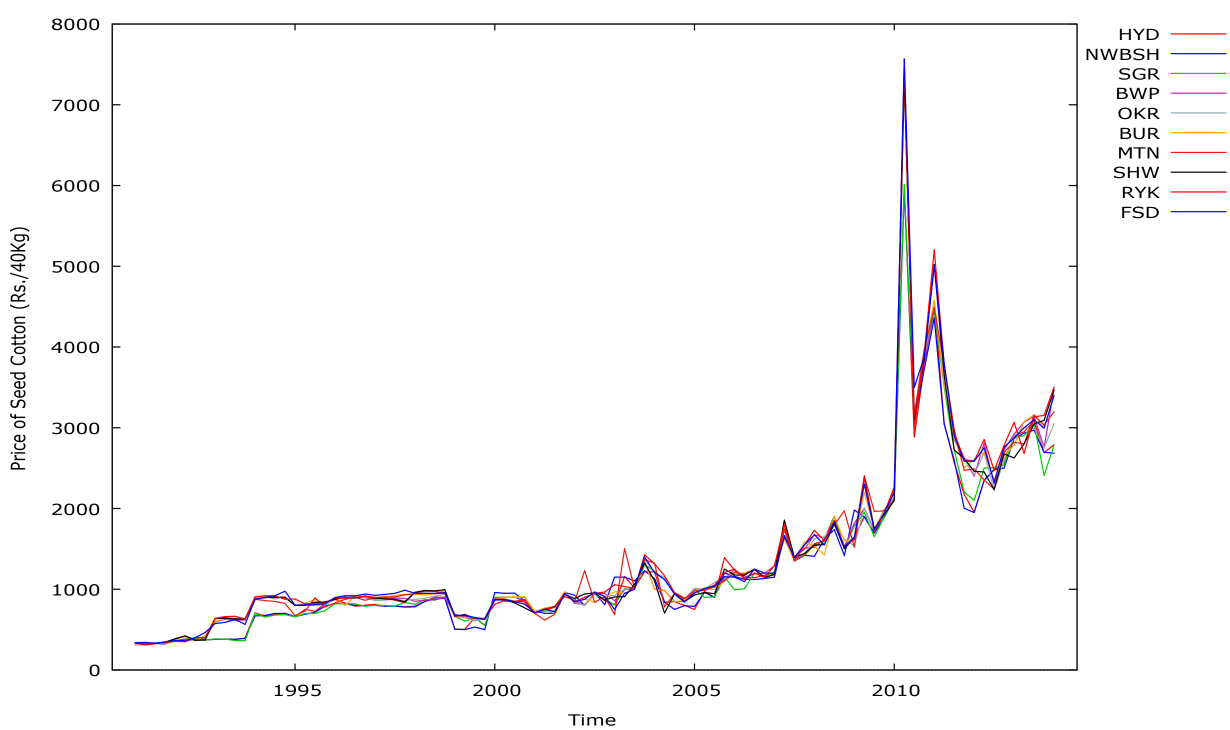

Figure 2 Quarterly price of seed cotton in major cotton producing districts of Pakistan

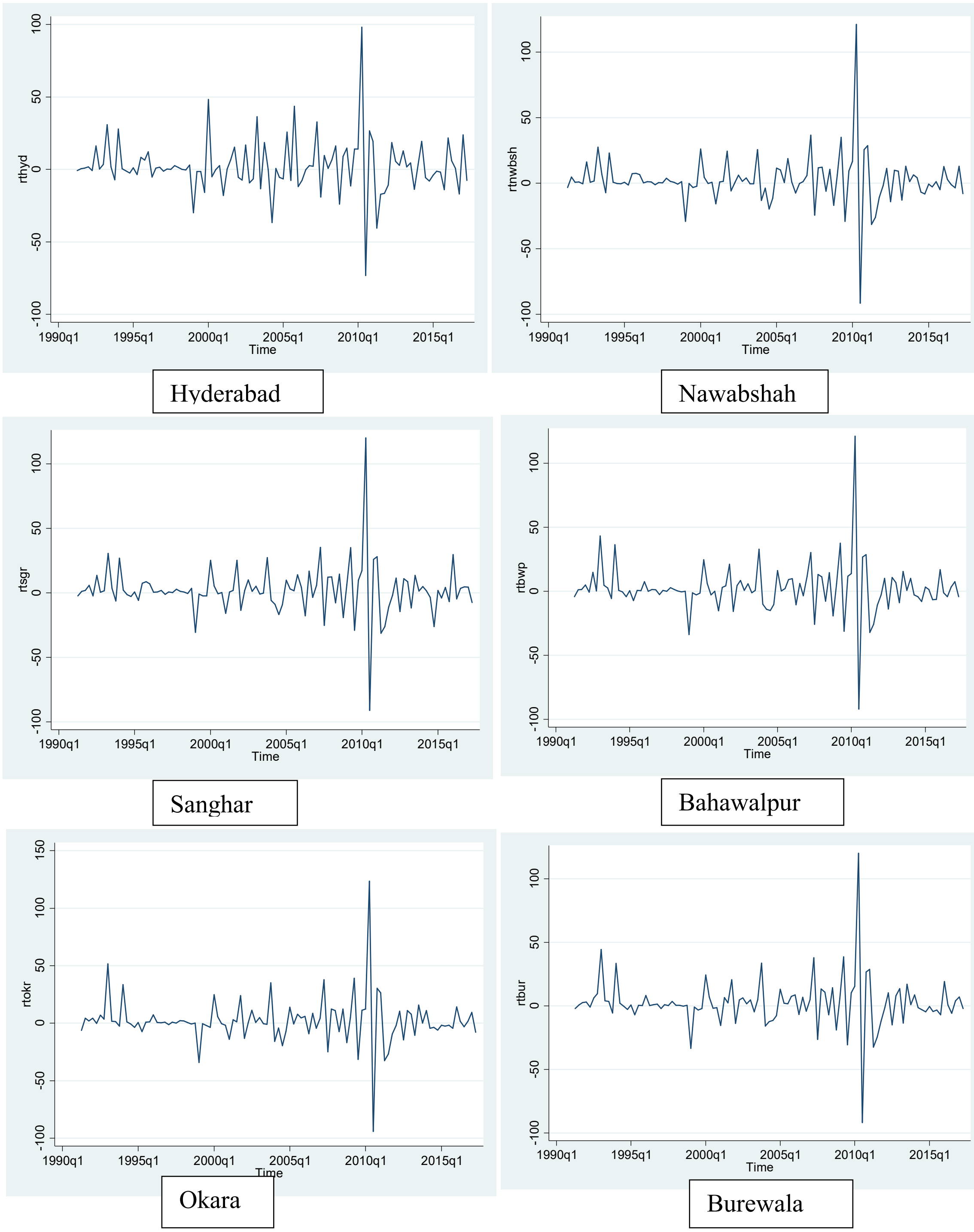

Figure 3 (a) Graphical depiction of price returns in various seed cotton markets of Pakistan

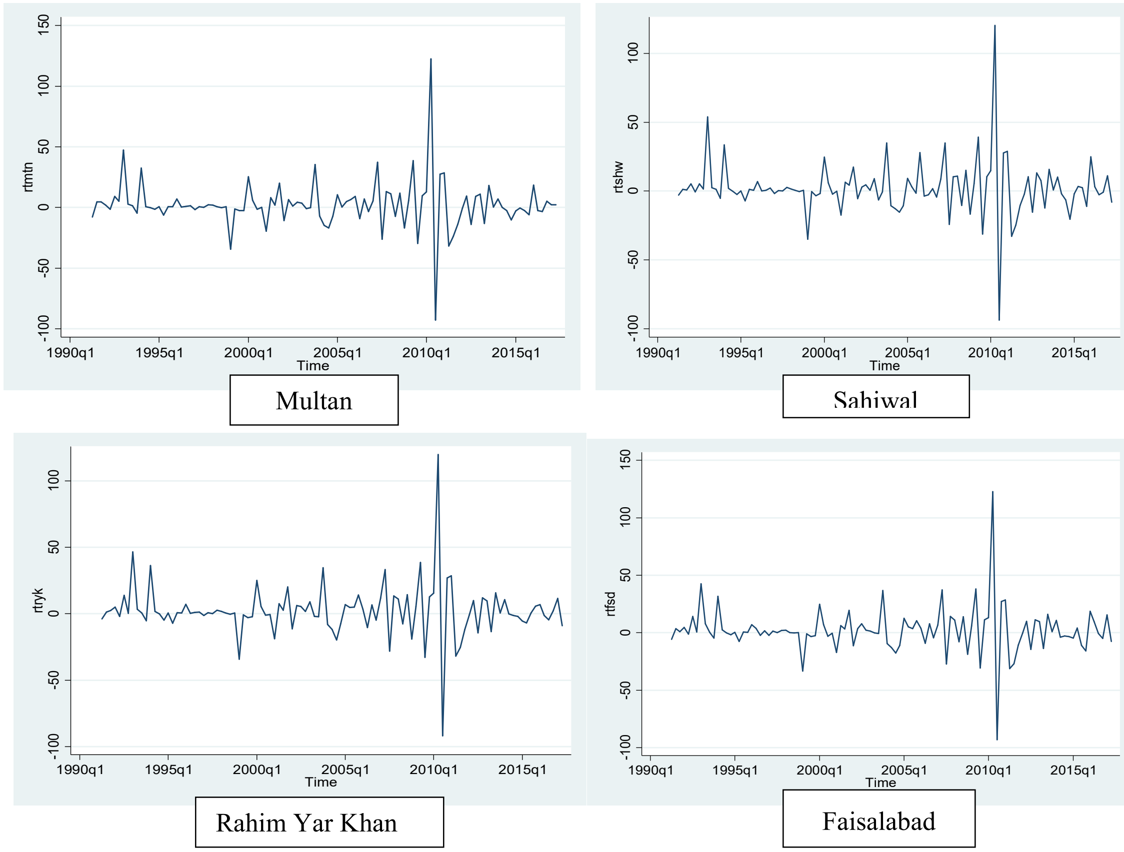

Figure 3 (b) Graphical depiction of price returns in various seed cotton markets of Pakistan

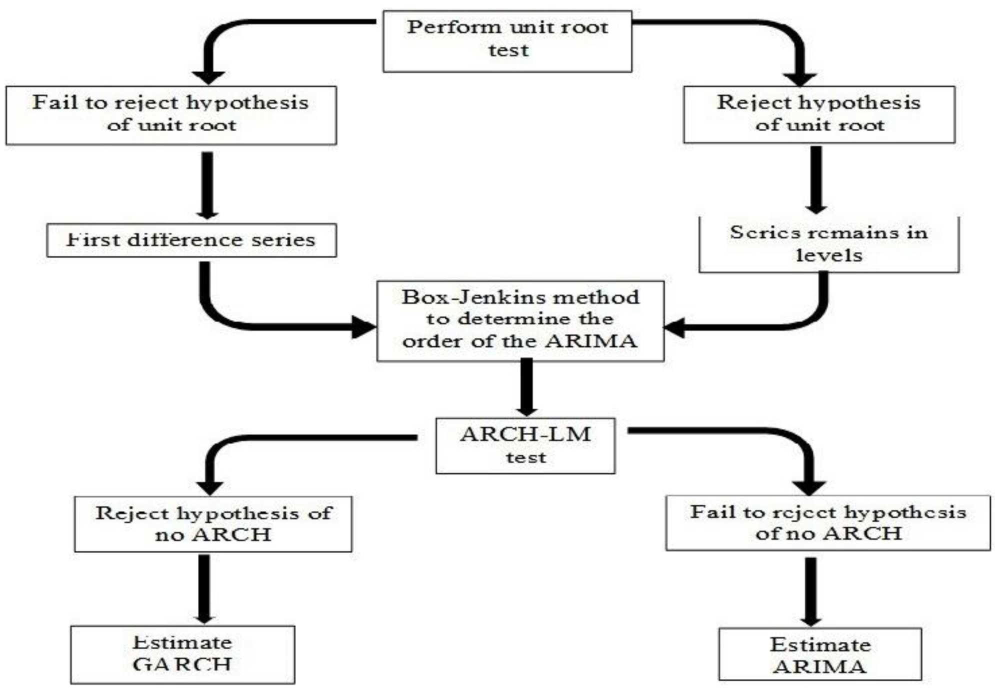

Figure 4 Flowchart of methodology to compute conditional volatility
Source: (Moledina *et al*., 2004)

Conclusion: This study uses the price data for ten major cotton markets for Pakistan including seven markets from Punjab and three markets from Sindh province. We employed volatility transmission analysis to examine the relationship between domestic seed cotton markets at second moment (variance) level. We come to the conclusion that there is positive dynamic conditional correlation among all the cotton market pairs and that the volatility of each cotton market is time varying. It is concluded that cotton markets in Pakistan transmit the abrupt price fluctuations which calls for the need of government intervention so as to stabilize the prices at the time of need and also support the farmers against risk. Cotton hedge trading would help in cotton price risk management. Investment in infrastructure including roads and transportation may also reduce price risk across markets. Role of middlemen should also be minimalized so that market forces can freely interact to set price and producers get their right profit. Current system of generalized subsidies should be replaced with targeted subsidies to indigent producers so as to avoid leakage of benefits to non-deserving. Keeping in view the importance of cotton crop for a country like Pakistan and knowing the significance of price volatility, our future research will focus on welfare impact of cotton price volatility on the market stakeholders. Such study will further aid in understanding the impacts of price fluctuations and would help the policy makers to device efficient policies in order to support the cotton economy of Pakistan.

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