Supply Response in Rainfed Agriculture of Odisha, Eastern India: A Vector Error Correction Approach

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Abstract

This paper provides an empirical investigation of supply response in case of rice in rainfed agriculture of Odisha. A composite weather index, instead of rainfall has been incorporated in the model to monitor farmers' supply response to weather. The vector error correction approach which avoids the unrealistic assumption of fixed supply on the basis of static expectation is applied. The empirical results reveal the fact that there is price inelasticity of supply whereas the supply elasticity with respect to weather is found to be very high. The policy implications suggest that there should be huge emphasis on irrigation as well as weather insurance. Assured irrigation minimizes the dependence on weather conditions and secures the crop from the vagaries of monsoon and thereby reduces the risk attached with farming.

Key Words: *Supply response, Weather index, Error correction modeling*

JEL Classification: *C32, C51, Q11*

Introduction

The study of farmer's response and price elasticities has become a vital area of research since it is well established that the price mechanism plays a significant role in bringing both demand and supply for agricultural goods in equilibrium and correcting the imbalances (Lahiri and Roy, 1985; p.315). The role of other shifters in supply response analysis like weather, irrigation, area under HYVs and other inputs along with price cannot be ignored since the information about supply elasticity allows for the effective formulation of appropriate agricultural policies and helps predict short-run and long-run input changes on production (Moula, 2010; p.182). In India, the results of supply response studies are inconclusive as they vary from crop to crop, region to region as well as from one methodology to another. The studies in Indian agriculture like Krishna (1963), Narayanan and Parikh (1981), Lahiri and Roy (1985), Kumar and Rosegrant (1997), Gulati and Kelley (1999), Kanwar (2004) and so on conclude differently so far as the supply response to price is concerned. Krishna (1963) in that context was an outstanding one in the sense that it refuted the widely prevalent view that the peasants in

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underdeveloped countries do not respond or respond very little or negatively to price movements. Since then, many people have studied the nature of price responsiveness of Indian farmers in the case of different crops using different methodologies. Unfortunately all these studies suffer on several grounds. One such lacuna is that they all treated the farmers alike, ignoring the type of physical conditions that they operate in. Since most of the studies are based on aggregate data in the all India level, they overlook many peculiarities at regional levels. Some farmers operate in conditions where irrigation and other facilities are well facilitated. Thus, their reaction to price varies from the farmers who operate in rainfed agriculture. In fact, the farmers in rainfed agriculture respond more to weather conditions rather than price. Hence, analyzing the supply response on aggregate level ignores the regional specific characteristics. Second, most of the studies utilized ordinary least square (OLS) estimation technique which is not an appropriate one[3]. Advances in time series techniques like Cointegration and Error Correction Mechanism (ECM) are more suitable in this regard. Error correction model performs well empirically and importantly it offers a scope of including the variables at levels alongside their differences and hence of modeling long-run as well as short-run relationships between integrated series[4]. The modeling of the short-run dynamics is consistent with any such long-run relationships (Hallam and Zanoli, 1993). Third, rainfall or rainfall index as a proxy for weather is incorporated commonly in a linear fashion along with prices and other shifters. But it is fairly established that both rainfall and temperature together affect the crop yields and also acreage devoted to cultivation[5]. Farmers make allocation of their land on the basis of soil moisture level which is partly determined by rainfall of last season and current temperature (Yu et al., 2012; p 372).

In this paper, we analyze the yield and acreage response in rainfed agriculture of Odisha to relative price and weather, taking care of aforesaid loopholes in the past studies. Odisha is one of the major rice producing states of India and agriculture in this state is considered as rainfed since more than 60 percent of cultivated area is still dependent upon rainfall (Chand et al., 2010). For this study, rice has been chosen since it is the staple food and major crop grown in all three seasons in Odisha. The cropping pattern is highly skewed towards rice (Lenka, 2010). Aridity index suggested by Oury (1965) is included as a proxy for weather variable which is a composite index of both rainfall and temperature. The aridity index is a better proxy for weather variable as it can be used to differentiate moisture condition of soil from one location to another at a particular point of time and reflects influence of weather on crops over the periods when taken historically. Most importantly it also allows law of diminishing returns in production process (Paltasingh et al. 2012). However, two specific objectives of the present paper are: (i) to

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3 Though the studies like Kumar and Rosegrant (1997), Gulati and Kelley (1999) and Kanwar (2004) used pooled time series data considering some Indian states, they did not use the method of cointegration and error correction mechanism which captures dynamic behaviour of supply response without loss of any generality. Few studies like Deb (2003), Tripathi (2008) used the cointegration and error correction technique to study supply response of Indian farmers at aggregate level. Again when it comes to the case of Odisha, not a single study has been undertaken.

4 The details about the loopholes of OLS technique and ECM as an improvement over it have been discussed in the third section dealing with estimation techniques.

5 In this aspect Lahiri and Roy (1985) was an improvement but still they ignored temperature while rainfall was systematically modeled.

estimate the supply response function for rice using Vector Error Correction model (VECM) and analyze both short-run and long-run elasticities of price and weather for effective policy implications, and (ii) to justify the use of an aridity index in measuring the elasticity of weather response of crop in such a way that the complete information regarding the weather influence on crop yield can be obtained. The paper is organized as follows: after a brief introduction, the second section discusses the theoretical background of the study. The third section describes the estimation techniques. Fourth section elaborates the model specification, data sources and the construction of study variables in the next section. Fifth section explains the empirical results of the model and finally the paper concludes with some policy implications.

Theoretical Framework

In the literature, broadly two types of methodologies are found to be used in analyzing the supply response behavior of farmers in agriculture, viz., one, the Nerlovian direct reduced form approach and second, the indirect structural form approach. The structural form approach shows the supply function derived from the profit maximizing framework. Just (1993) and Sadoulet and de Janvry (1995) have surveyed extensively the studies using this approach. It requires detailed input and output prices, quantities of inputs and outputs etc. But the agricultural market structure in India is not much developed and does not function in a competitive environment of profit maximizing framework. The sophistication and availability of data in detail is another problem. Thus, majority of studies follow the Nerlovian reduced form approach. Nerlovian model is built to examine farmer's output reaction based on price expectation and partial adjustment (Nerlove, 1958). It is also flexible enough to incorporate non-price factors. It can be computed in terms of yield, area or output response. The model is expressed as the desired yield of a crop in period t is a function of expected relative prices P and exogenous shifters Z, which can be written as equation (1):

$$Y_t^* = \alpha_1 + \alpha_2 P_t^* + \alpha_3 Z_t + u_t \tag{1}$$

where Y_t^* is the desired cultivated area in period t; P_t^* is expected relative prices of the crop and of other competing crops; Z_t is a set of other exogenous variables including the climatic, physical and institutional factors. u_t takes into accounts those unobserved random factors affecting the area under cultivation. α_s (s =1, 2, 3) are long-run coefficients to be estimated. Specifically, α_2 is the long-run coefficient of supply response.

Partial Adjustment and Adaptive Expectation

Farmers' response is constrained by many factors like small land holding combined with the need to diversify production to minimize risk, credit constraint, lack of availability of inputs and so on (Moula, 2010). Apprehension regarding the uncertainty of weather plays an important role. Thus, full adjustment in desired position within a short span of time is subject to those constraints. In order to incorporate that possibility in the cultivation process, it is assumed in Nerlovian tradition that the change in yield between two periods occurs in proportion to the difference between the expected output for current period and actual output in previous period. Thus, the model can be written as given below:

$$Y_t - Y_{t-1} = \delta\left(Y_t^* - Y_{t-1}\right) + \epsilon_t;\;\; 0 \le \delta \le 1 \tag{2}$$

$$Y_t = \delta Y_t^* + (1-\delta)Y_{t-1} + \epsilon_t \tag{3}$$

When it comes to expectation, it is generally understood that the price farmers expect to prevail at the harvesting time cannot be observed. Therefore, one has to form expectation based on actual and past prices. In Nerlovian tradition, adaptive expectation implies that the farmer revises his expectations by some proportion of the extent by which his expectation in the last period differed from actual (Lahiri and Roy, 1985). Thus, the model can be written as given below:

$$P_t^* - P_{t-1}^* = \lambda\left(P_{t-1} - P_{t-1}^*\right) + \varepsilon_t;\;\; 0 \le \lambda \le 1 \tag{4}$$

$$P_t^* = \lambda P_{t-1} + (1-\lambda)P_{t-1}^* + \varepsilon_t \tag{5}$$

where P_t^* is expected relative price at t, P_{t-1}^* is expected relative price at t-1 and P_{t-1} is actual price in previous period. λ is adjustment coefficient. If λ is one, then it becomes static expectation where expected price of current year equals to the preceding year price.

Now the unobservable Y_t^* and P_t^* are eliminated from the system by substituting equation (1) and (5) into (3), and with little algebraic manipulation, the final reduced form equation comes out as follows:

$$Y_t = \beta_1 + \beta_2 P_{t-1} + \beta_3 Y_{t-1} + \beta_4 Y_{t-2} + \beta_5 Z_t + e_t \tag{6}$$

where $\beta_1 = \alpha_1\delta\lambda$; $\beta_2 = \alpha_2\delta\lambda$; $\beta_3 = (1-\delta)+(1-\lambda)$; $\beta_4 = -(1-\delta)(1-\lambda)$; $\beta_5 = \alpha_3\delta$ and $e_t = \epsilon_t - (1-\lambda)\epsilon_{t-1} + \delta u_t - \delta(1-\lambda)u_{t-1} + \alpha_2\delta\varepsilon_t$. This estimable reduced form equation is called the distributed lag model with lag dependent variable as independent variable. The β coefficients except that of lagged dependent variable show short-run elasticities if taken in logarithm form. Long-run elasticities are obtained by dividing the short-run elasticities by an adjustment coefficient, i.e., one minus coefficient of one-lagged dependent variable $(1-\beta_3)$.

Estimation Technique: Cointegration and Vector Error Correction Mechanism[6]

The Nerlovian mechanism assumes that the adjustment coefficient (δ) is less than one. So the fluctuation in expected output level is less than the fluctuation in observed

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[6] The methodology of cointegration and error correction mechanisms can be found in Engle and Granger (1987), Banerjee et al. (1993), Hallam and Zanoli (1993), Hwang (2002), Deb (2003), Awosola et al. (2006) and so on.

output level such that the actual change in output level between period t and t-1 is only a fraction of the change required to achieve the expected output level. In this case, the only condition for observing significant differences between short-run and long-run elasticities is the introduction of non-static assumption. Therefore, it is biased and the studies employing this mechanism have mostly found low values, sometimes even zero for long-run elasticities (Awosola et al., 2006). Thus, the methodology of Cointegration and Error Correction Mechanism (ECM) are favoured over the ordinary least square (OLS) estimation method of Nerlovian framework. Apart from this, the OLS technique uses the time series data which are very often suspected to be non-stationary since most of the economic data series have unit root problem. So the statistical significance of t-test and F-test etc. loses relevance (McKay et al., 1998). But the advanced time series methodology of Cointegration can be used with nonstationary data to avoid spurious regression (Banerjee et al., 1993). When combined with this the ECM, considering the partial adjustment and adaptive expectation of farmers which are fundamental in the analysis of agricultural supply response, gives distinct long-run and short-run elasticities among variables (Townsend and Thirtle, 1995). Moreover, the partial adjustment model is nested within the error correction mechanism. Steps are briefly explained below:

First, the data series for each variable is tested for stationarity by using Augmented Dicky-Fuller (ADF) statistics (Dicky and Fuller, 1981) and the lag length is chosen that ensures the residual is empirically white noise. The regression equation for ADF is expressed as follows:

$$\mathit{\Delta} Y_t = \mu_0 + \mu_1 t + (\delta - 1)Y_{t-1} + \sum\nolimits_{i=1}^{k} \psi_i \mathit{\Delta} Y_{t-1} + e_t \tag{7}$$

where e_t is pure white noise error term and k is chosen lag length. The null hypothesis H_0 holds that $\mu_1 = 0$ against alternative hypothesis H_1 that. If the H_0 is rejected statistically then the series (Y) is stationary. If not, the first difference is taken to make it stationary. Testing for stationarity is necessary to determine whether the model follows a ‘Differenced Stationary Process’ (DSP) or a ‘Trend Stationary Process’ (TSP). The distinction between DSP and TSP is important since variables following different stationary processes cannot be co-integrated (Tzouvelekas et al., 2001). Once the stationarity of individual series is established, the linear combination of integrated series are tested for cointegration. If they are cointegrated, it implies a longrun equilibrium relationship. The cointegration analysis is carried out by applying Johansen test.

Johansen Method of Cointegration

Johansen (1988) and Johansen and Juselius (1990, 1992) mechanism of cointegration in a multivariate framework is a form of VECM where only one cointegrating vector exists. Its parameters can be interpreted as the estimates of long-run relationship between the variables concerned. Suppose that Y_t is an (nx1) vector of non-stationary I(1) variables, then the unrestricted vector auto regression (VAR) of Y_t up to ‘k’ lags can be specified as:

$$Y_t = K + \sum\nolimits_{i}^{k} \mathit{\Pi}_i Y_{t-\iota} + e_t : \ t = 1,\ 2,\ \ldots,\ T \tag{8}$$

where Π_i is an (n x n) parameter matrix that measures the long-run effect of the respective lag levels of Y on its current level and e_t is an identically and independently distributed n-dimensional vector of residuals and is an (nx1) vector of constants. The first-difference of equation (8) is used to formulate the error correction representation of Y_t as:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{k-1} \Delta Y_{t-k+1} + \Pi Y_{t-k} + u_t \tag{9}$$

where $\Gamma_i = -(I - \Pi - \ldots - \Pi_i)$; $i = 1, 2 \ldots k-1$, $\Pi = -(1 - \Pi_1 - \ldots \Pi_k)$

Γ_i 's are $(n \text{ x } n)$ coefficient matrix for

Π is an (n x n) coefficient matrix for the variables in Y_{t-k},

u_t is an (nx1) column vector of disturbance terms.

The estimates of Γ_i and Π provide the information regarding the short-run and long-run adjustments to the changes in Y_t respectively. The cointegration analysis primarily tests the impact matrix to gather information on the long run relationship(s) among variables contained in the Y_t vector. If the rank of Π matrix (r) is equal to zero, the impact matrix is a null vector thereby implying that there is no cointegration at all, since there is no linear combination of Y_t that are I(0). In this case, the VAR in first differences is suitable involving no long-run elements. If Π has a full rank (i.e., $r = n$), then the vector process of Y_t is stationary. It implies that there is no problem of spurious regression and the appropriate modeling strategy is to estimate the traditional VAR in levels. But, in case of $0 < r < n$, there exists 'r' cointegrating vectors. It says that 'r' linearly independent combinations of the variable in Y_t are stationary along with (n-r) non-stationary vectors. The coefficient matrix can be factored into, where both 'α' and 'β' are (n x r) matrices of rank r ($0 < r < n$) and β^I is the transpose of β. The cointegrating vector β has the property that $\beta^I Y_t$ is stationary even if Y_t itself is nonstationary. The matrix 'α' measures the strength of the cointegrating vector as it represents the speed of adjustment to disequilibrium. The Johansen approach provides two test statistics for the number of cointegrating vectors: the trace and maximum Eigen value tests. The trace statistic tests whether the number of cointegrating vectors is less than r (r = 0, 1, 2 . . .) whereas the maximum Eigen value statistic tests whether the number of cointegrating vectors is r = 0 (or r = l, r =2 . . .) against the alternative r = l (or r =2, r =3 . . .).

Vector Error Correction Mechanism

Once the cointegration among the variables is established, the ECM is used to analyze the short-run and long-run dynamics in the model. It has two distinct characteristics: first, an ECM is dynamic in the sense that it involves lags of the dependent and explanatory variables; it thus captures the short-run adjustments to changes of particular adjustments into past disequilibria and contemporaneous changes in the explanatory variables. Second, the ECM is transparent in displaying the cointegrating relationship between or among the variables.

VEC framework of agricultural supply response is as follows:

$$\Delta Y_t = c_1 + \rho_y e_{t-1} + \sum_{i=1}^{k} \rho_{11}(l)\Delta Y_{t-i} + \sum_{i=1}^{k} \rho_{12}(l)\Delta P_{t-i} + \sum_{i=1}^{k} \rho_{13}(l)\Delta Z_{t-i} + e_{1t} \tag{10}$$

$$\Delta P_t = c_2 + \rho_p e_{t-1} + \sum_{i=1}^{k} \rho_{21}(l)\Delta Y_{t-i} + \sum_{i=1}^{k} \rho_{22}(l)\Delta P_{t-i} + \sum_{i=}^{k} \rho_{23}(l)\Delta Z_{t-i} + e_{2t} \tag{11}$$

$$\Delta Z_t = c_3 + \rho_z e_{t-1} + \sum_{i=1}^{k} \rho_{31}(l)\Delta Y_{t-i} + \sum_{i=1}^{k} \rho_{32}(l)\Delta P_{t-i} + \sum_{i=1}^{k} \rho_{33}(l)\Delta Z_{t-i} + e_{3t} \tag{12}$$

where, $e_{t-1} = Y_{t-1} - \beta_1 P_{t-1} - \beta_2 Z_{t-1}$ is the error correction term (ECT) and β_1, β_2 are parameters of the cointegrating vector and e_{1t}, e_{2t} and e_{3t} are the white noise disturbances. The ECT expresses the long-run causal effects, while the coefficients of lagged explanatory variables give an indication of short-run adjustments. The coefficient of ECT must be negative and significantly different from zero. Being negative implies that if there is a deviation from the current and long-run levels, there would be an adjustment back to long-run equilibrium in subsequent periods to eliminate the disequilibrium (Hwang, 2002; Awosola et al., 2006).

Data Sources and Variables

The study undertakes the investigation of supply response in case of yield and acreage of rice. The yield and acreage functions are defined below as follows:

$$Y = f\left({p_1}/{q}, GIR,\ W_{g,} \right) \tag{13}$$

$$A = g\left({p_1}/{p_2}, F, W_{s,} \right) \tag{14}$$

where Y is yield of rice (kg/ha), p_1, p_2 and q are output prices of rice, competing crop (here maize) and fertilizer respectively. GIR is gross irrigated area under rice (000'ha), and F is total fertilizer consumption (000' ton). W_g and W_s are growing period and sowing period weather index respectively[7]. All the variables are constructed from secondary data for 31-year time period of 1980- 2010. The data on yield acreage, irrigated area and fertilizer consumption are collected from various issues of the 'Odisha Agricultural Statistics' published by Directorate of Agriculture and Food Production, Government of Odisha. The Centre for Monitoring Indian Economy (CMIE) database also serves as a useful source. The minimum support prices published by Commission for Agricultural Costs and Prices (CACP), Government of India are taken as proxy for price variables. The climatic data like rainfall and temperature are collected from India Meteorological Department (IMD), Pune and also from the website 'http://indiawaterportal.org/metdata' developed by School of Environmental Sciences, University of East Anglia, U.K. To account for weather influence in supply response

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7 The growing period of rice consists of three months like June, July, and August and the sowing period consists of May and June. So while constructing weather index for two periods we take the monthly average of rainfall and temperature for that period.

analysis we use the Angstrom aridity index[8]. This index is constructed by using monthly figures of rainfall and temperature and it is defined as:

$$W_i = {R_i}\Big/{1.07^{T_i}}\,;\ i = 1, 2 \ldots n \tag{15}$$

Both R_i and T_i indicate growing period or sowing period rainfall and temperature respectively of i[th] year[9]. Out of total cultivated area farmers have to decide on the proportion to be allocated to rice. The decision on acreage is determined in part by anticipated relative price $\left({p_1}/{p_2} \right)^*$ since the output prices and input prices are uncertain at the time of sowing. Once the acreage decision is taken, yield depends on relative price of output, i.e., relative to the input price $\left({p_1}/{q} \right)^*$ which is uncertain. Yield also gets influenced by the portion of irrigated area under rice. Fertilizer consumption and irrigated area are incorporated as the proxy for market accessibility and technological transformation. Both fertilizer and irrigation are not included in one equation because of possible colinearity between them.

Results and Discussion

The results of unit root test are reported in Table 1. As shown by the ADF test, we do

Table 1: *Unit Root Test for the Data Series*

Series	*Level*	*1st Difference*	*M - Values*			*Conclusion*
			1%	*5%*	*10%*	
Yield (Y)	-1.15	-9.64***	-3.68	-2.97	-2.62	I (I)
Acreage (A)	-2.18	-6.56***	-3.67	-2.96	-2.62	I (I)
Price (P_1/q)	-1.57	-3.21**	-3.68	-2.97	-2.62	I (I)
Price (P_1/p_2)	-1.45	-3.38**	-3.67	-2.96	-2.62	I (I)
GIR	-1.06	-6.17***	-3.70	-2.97	-2.62	I (I)
Fertilizer (F)	-0.04	-7.14***	-3.68	-2.97	-2.62	I (I)
W_g	-5.15***	…	-3.67	-2.96	-2.62	I (0)
W_s	-6.32***	…	-3.67	-2.96	-2.62	I (0)

Notes: (i) ***, ** and * denote rejection of hypothesis of a unit root at 1% , 5% and 10% level respectively.
(ii) The value of k is determined by using Akaike's AIC criterion.
(iii) Instead of t-statistics, Mackinnon critical values denoted by M-Values have been applied here.

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8 Out of many aridity indexes suggested by Oury (1965), Angstrom index is generally widely used for economic analysis (Zhang and Carter, 1997). It has been proved that Angstrom index performs better than others (Paltasingh et al., 2012).

9 The monthly temperature figures are compiled by taking the monthly average of daily maximum temperature. Unlike Yu et al. (2012), we have taken the maximum temperature figures. The reason for taking maximum temperature is spawned from the fact that India is a hot country and maximum temperature rather than minimum or mean temperature affects the crop yield.

not reject the null hypothesis that the level of each series is generated by a random walk process except the weather index variables (W_g and W_s). But the hypothesis of a random walk in the first difference of those series is rejected. It implies that the series integrated of order one cannot be estimated by the standard OLS technique and VEC is the better option in this respect. However, before applying VEC model we need to ensure that the series of same order of integration are co- integrated. Therefore, we apply Johansen (1988) cointegration test before applying VEC model. The contegration test also provides the long-run equilibrium relationship and thereby the long-run elasticity of supply response. The results of cointegration for two equations, i.e., yield and acreage functions as aforementioned are reported in Table 2 and 3.

Table 2: *Cointegration Test (Y, P and GI)*

Hypothesis	***Eigen Values***	***Trace Statistics***	***5% Critical Value***	***Prob.***	***Max. Eigen Stat.***	***5% Critical Value***	***Prob.***
H_0: r = 0; H_1:r>0	0.6620	38.234**	29.7971	0.0042	28.2053**	21.13162	0.0043
H_0: r = 1; H_1:r>1	0.2902	10.0291	15.4947	0.2785	8.915437	14.26460	0.2933
H_0: r = 2; H_1:r>2	0.0419	1.11374	3.84146	0.2913	1.113744	3.841466	0.2913

Notes: Trace statistics and Max Eigen values indicate one cointegrating equation at 5% level. The symbol ** denotes rejection of hypothesis at 5% level. Here P is relative price of rice P_1 to input q, i.e., P/q.

Table 3: *Cointegration Test (A, P and F)*

Hypothesis	***Eigen Values***	***Trace Statistics***	***5% Critical Value***	***Prob.***	***Max. Eigen Stat.***	***5% Critical Value***	***Prob.***
H_0: r = 0; H_1:r>0	0.6858	37.5925**	29.7971	0.0052	28.9488**	21.13162	0.0032
H_0: r = 1; H_1:r>1	0.2767	8.64368	15.4947	0.3994	8.10143	14.26460	0.3685
H_0: r = 2; H_1:r>2	0.0214	0.54224	3.84146	0.4615	0.54224	3.841466	0.4615

Notes: Trace statistics and Max Eigen values indicate one cointegrating equation at 5% level. The symbol ** denotes rejection of hypothesis at 5% level. Here P is the relative price (p_1/p_2).

Testing of the cointegration among two sets of variables is done by using Johansen-Juselius (1990) procedure with the Trace statistics and maximum Eigen values. One combination shows the yield function that includes Y, P and GIR, while the other combination representing acreage function, includes A, P and F. The relative price P is different for yield equation and acreage equation. Both tests reject the hypothesis of more than one cointegrating vector at 5 percent level indicating that there exists a unique cointegrating vector between the variables concerned in case of yield function (Table 2). The optimal lag length (determined by using Akaike's FPE) is three lags for both the combinations. When only one cointegrating vector exists, its parameters can be interpreted as estimates of long-run cointegrating relationship between the variables concerned (Hallam and Zanoli, 1993). Thus the yield model has one cointegrating vector. The normalized cointegrating equation for yield of rice is as follows.

$$Y = -1741.55 + 59939.27P^{**} + 0.5116GIR \tag{16}$$

The coefficient of price is significant at 5 percent level while the coefficient of gross irrigated area under rice is not significant. The longrun supply elasticity of price with respect to yield comes as 0.36 at mean while that of irrigation comes as 0.59. It shows that in rainfed agriculture, irrigation is must in order to integrate farmers to the market. Unless there is assured irrigation, the farmers are always dependent on weather conditions which are highly erratic and uncertain.

The cointegrating relation between acreage, price and fertilizer is also tested here and results are shown in Table 3. The maximum Eigen value and trace statistics reject the null hypothesis of more than one cointegrating vector among the variables at 5 percent level. The normalized cointegrating equation reflecting the longrun equilibrium relationship between acreage and other variables is as follows.

$$A = -3116.72 + 0.8813P + 12.16F^{***} \tag{17}$$

The coefficient of price is positive but not statistically significant. It implies that the acreage behavior of farmer in rainfed agriculture is not price driven. Instead of price, the weather and fertilizer appear to be more determining factor in the long run. The coefficient of fertilizer is in line with the theoretical expectation and significant at 1 percent level. The supply of fertilizer at affordable price acts as an adequate incentive to the farmers to go for extensive cultivation in the longrun. It also shows the market accessibility by the farmers.

Table 4 shows the VECM estimates of supply response of rice yield to real relative price as well as to gross irrigated area and weather. The model fits better as the adjusted R-squared is 0.65 and F-statistics is also well above the 1% significance level. It can be observed from the result that the coefficient of price is significant at 10% level. The coefficient of irrigated area is not significant but retains the theoretical positive sign. The coefficient of weather is significant at 1% level showing how significantly weather influences. The significance of negative error correction coefficient (-0.6105) as expected, suggests that about 61% of deviation from long run equilibrium is made up within one time period. It also implies that the speed with which price of rice adjusts from short run disequilibrium to changes in rice supply in order to attain long run equilibrium is 61% within one year. Calculation of short run price elasticity at mean renders the result as 0.37 while the elasticity of yield to weather is 0.63 which is significant at one percent level. Thus, it implies that yield in short run is more detected by weather than price in backward rainfed agriculture. The coefficient of gross irrigated area under rice is positive but not significant. Though irrigation is a potent stimulus but in the shortrun farmers are unable to increase the area under irrigation that probably leads to insignificant impact of irrigation on yield. However, the importance of this variable in rainfed agriculture cannot be undermined. The shortrun elasticity of yield with respect to irrigation comes as 0.46 percent.

Similarly, the VECM results for acreage response are depicted in Table-5. The coefficients of price and fertilizer are not significant but the weather comes out to be a significant factor influencing acreage behavior of rice. The model does not fit well since the adjusted R-squared value is very low so also the F-statistics. However, the error correction coefficient showing the speed of adjustment towards the longrun equilibrium is negative as expected and highly significant. It implies that about 11% of deviation is

Table 4: *VECM Estimates of Yield Response Function*

Error Correction:	***Δ(Y)***	***Δ(P)***	***Δ(GI)***	***Δ(W_g)***
CointEq1	-0.6105***	6.48E-07	0.073785	-0.0197***
	[-4.02626]	[0.55430]	[0.62852]	[-3.33225]
Δ(Y(-1))	-0.45231**	-2.86E-07	-0.41869***	0.008910
	[-2.23846]	[-0.18341]	[-2.67635]	[1.13103]
Δ(Y(-2))	-0.06998	6.46E-10	-0.1507	-0.00341
	[-0.38220]	[0.00046]	[-1.06311]	[-0.47728]
Δ(P(-1))	60996.64 *	-0.14021	-71078.4***	941.0561
	[1.77323]	[-0.52838]	[-2.66892]	[0.70171]
Δ(P(-2))	29730.05	0.001397	52685.69*	-423.04
	[0.77943]	[0.00475]	[1.78408]	[-0.28448]
Δ(GI(-1))	0.136972	-3.97E-07	-0.60103***	-0.01283
	[0.53428]	[-0.20092]	[-3.02813]	[-1.28353]
Δ(GI(-2))	0.296851	3.32E-07	-0.3711**	-0.00058
	[1.30299]	[0.18887]	[-2.10395]	[-0.06572]
Δ(Wg(-1))	73.44298***	-4.95E-05	5.608227	0.320623
	[3.56657]	[-0.75119]	[0.84865]	[0.96348]
Δ(Wg(-2))	14.76040**	-3.42E-05	-2.94352	0.518065**
	[2.15889]	[-0.64758]	[-0.55608]	[1.94357]
C	54.76240**	-0.00036**	57.96449***	0.303233
	[2.17711]	[-1.85806]	[2.97644]	[0.30921]
R-squared	0.777367	0.102120	0.710315	0.629297
Adj. R-squared	0.659503	-0.37323	0.556952	0.433043
F-statistic	6.595440	0.214833	4.631597	3.206536
Log likelihood	-156.302	161.5538	-149.392	-68.6993
Akaike AIC	12.31865	-11.2262	11.80684	5.829581
Schwarz SC	12.79859	-10.7463	12.28678	6.309521

Notes: The symbols ***, ** and * indicate the significance level at 1%, 5% and 10% respectively.
The figures within [ ] indicate t-statistic values.

being corrected in one year. The coefficient indicates a feedback of about 11% of previous year's disequilibrium from the longrun elasticity of relative price of rice. The coefficients of relative price and that of fertilizer are not significant. But weather condition of sowing period has a negative impact on acreage behaviour. The rainfall during sowing period beyond optimum level hinders the soil preparation and area under cultivation ultimately and so also temperature.

***Table 5:** VECM Estimates of Acreage Response Function*

Error Correction:	***Δ(A)***	***Δ(P)***	***Δ(Ws)***	***Δ(FRT)***
CointEq1	-0.10702***	-0.00503	0.007890	0.040188
	[-2.84001]	[-0.49955]	[1.24786]	[2.38808]
Δ(A(-1))	-0.4218**	-0.01601	-0.04597	-0.08621
	[-1.71931]	[-0.24407]	[-1.11674]	[-0.78684]
Δ(A(-2))	0.009018	-0.05657	-0.01352	-0.07334
	[0.03631]	[-0.85214]	[-0.32435]	[-0.66130]
Δ(P(-1))	0.055985	0.463966	-0.14611	0.074889
	[0.06221]	[1.92860]	[-0.96759]	[0.18633]
Δ(P(-2))	1.825707	0.472112	0.083468	-0.1704
	[1.32436]	[1.28119]	[0.36086]	[-0.27678]
Δ(Ws(-1))	-4.15546**	0.080807	-0.43619	1.821263
	[-2.28657]	[0.16634]	[-1.43048]	[2.24405]
Δ(Ws(-2))	-1.51436	0.358550	-0.12676	1.359093
	[-1.14838]	[1.01718]	[-0.57288]	[2.30780]
Δ(FRT(-1))	-1.01979	-0.29246	0.025147	-0.07156
	[-1.51950]	[-1.63026]	[0.22331]	[-0.23875]
Δ(FRT(-2))	-0.97138	-0.35625	0.016720	0.257133
	[-1.59722]	[-2.19144]	[0.16385]	[0.94674]
C	22.58748**	2.587602	1.267557	2.219113
	[1.98862]	[0.85226]	[0.66510]	[0.43748]
R-squared	0.391170	0.381908	0.581138	0.517300
Adj. R-squared	0.068849	0.054683	0.359388	0.261753
F-statistic	1.213602	1.167112	2.620685	2.024284
Log likelihood	-137.067	-101.444	-88.8709	-115.302
Akaike AIC	10.89387	8.255143	7.323771	9.281627
Schwarz SC	11.37381	8.735082	7.803711	9.761566

Notes: the symbols ***, ** and * indicate the significance level at 1%, 5% and 10% respectively.
The figures within [ ] indicate t-statistic values.

Table 6 reveals the shortrun and longrun elasticities of both yield and acreage function. The shortrun elasticity of weather is higher in comparison to price and other non-price factors in both functions though it is comparatively lower in magnitude in case of acreage function. Some past studies that used rainfall directly as a proxy do not come up with consensus that weather (rainfall) is vital factor in supply response analysis, particularly in case of Indian agriculture. However, some studies (Lahiri and Roy, 1985; Bapna et al., 1981; Mishra, 1998; Kanwar, 2004; Mythili, 2008; Tripathi, 2008) observed that rainfall is an important shifter while other studies (Deb, 2003; Rao, 2004; Devi et al., 1990; Kumar and Rosegrant, 1997 and so on) do not put much importance to it or it is found insignificant. But none of these Indian studies used weather index that takes into accounts both rainfall and temperature.

Table 6: *Long run and Short run Elasticities of Variables*

Yield response function		
Variables	***Shortrun elasticity***	***Longrun elasticity***
Price (p_1/q)	0.37	0.36
Irrigation	0.46	0.59
Weather	0.63	
Acreage response function		
Variables	***Shortrun elasticity***	***Longrun elasticity***
Price (p_1/p_2)	0.01	0.26
Fertilizer	-0.04	0.57
Weather	0.23	

Note: The elasticities are calculated at mean values.

Conclusion and Policy Implications

The estimates of elasticity of different variables presented in this study can be a useful addition to the repository of knowledge about supply elasticity of different agricultural commodities in India at aggregate level and regional level since the agriculture of Odisha is hardly being studied. They are hoped to help frame adequate policies for the agricultural sector of Odisha looking at the peculiar characteristics of the sector. From the analysis it is made clear that farmers' supply response to price varies from the very physical conditions that they operate in. Here in the case of rainfed agriculture of Odisha, utilizing dynamic time series techniques of cointegration and vector error correction model, it is found that for both yield and acreage behavior there has been price inelasticity of supply both in shortrun as well as longrun. But weather comes as the most dominating factor influencing both yield and acreage behavior in shortrun. The results of this study support other studies conducted at aggregate level or regional level like Palanivel (1995) and Kanwar (2004) which also concluded inelasticity of supply response to price and non-price factors like rainfall, irrigation, consumption of fertilizer, high yield variety seeds and infrastructure are highly significant in higher agricultural growth. Even Krishna (1963) in case of Punjab concluded that there are positive short run price elasticities but it varies from as low a figure as 0.1 to 0.4 in case of different commodities except cotton.

The study confirmed that non-price factors are more important and complementary to price. So, strategies that put more emphasis on non-price factors like irrigation, credit and adequate input supply at affordable price are crucial for policies promoting agricultural development. Apart from that agricultural research and extension should be strengthened and there should be a well linkage between farmers and input and output market since the lack of market in place sometimes compels the farmers to go for distress sale and subsequently they lack incentive to cultivate more or lend more acreage to cultivation. It has been argued that agricultural price inflation in India is largely supply-determined, resulting from crop failure and bad supply management due to bad monsoons. Though, the government policies towards procurement and price support programmes can also contribute to certain price fluctuations but it is paramount importance that the year-to-year revision in procurement prices should be enough to leave a mark on the agricultural price movements and encourage the farmers. The coping strategies against the aberrant weather condition should be strengthened by conducting workshops of farmers or strengthening the extension services. Many weather and abiotic stresses like flood, drought, early drought, cyclone and wind blow at different stages of crop growth cause the farmers heavy losses of crops. Therefore, the risk coping strategies should be framed accordingly and farmers' ability to cope with these stresses should be strengthened by integrating them with the market, providing them adequate advance information about those natural calamities and encouraging them to go for crop diversification. Declining public spending on infrastructure like irrigation is vital concern that should be addressed. Increasing area under irrigation makes the farmers less dependent on weather condition and can minimize the risk attached with cultivation. Moreover, it works as a panacea to many problems.

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References

Awosola, O. O., Oyewumi, O. and Jooste, A. (2006), "Vector Error Correction Modeling of Nigerian Agricultural Supply Response," *Agrekon*, 45(4): 421-436.

Banerjee, A., Dolado, J. J., Galbraith, J. W. and Hendry, D. (1993), *Co-integration, Error Correction, and the Econometric Analysis of Non-Stationary Data: Advanced Texts in Econometrics*, Oxford: Oxford University Press.

Bapna, S. L., Binswanger, H. P., and Quizon, J. B. (1981), "System of Output Supply and Factor Demand Equations for the Semi-Arid Tropical India," *Indian Journal of Agricultural Economics*, 39(2): 179-213.

Chand, R., Pandey, L. M., and Garg, S. (2010), "Rise and Decline of Rainfed Agriculture", in S. Singh and M.S. Rathore (ed), *Rainfed Agriculture in India: Perspectives and Challenges*, New Delhi: Rawat Publications.

Deb, S. (2003), "Terms of Trade and Supply Response of Indian Agriculture: Analysis in Cointegration Framework", Working Paper No. 115, Centre for Development Economics, Department of Economics, Delhi School of Economics, Delhi University, India.

Dickey, D. A. and Fuller, W. A. (1981), "Likelihood Ratio Statistics for Auto-regressive Time Series with a Unit root", *Econometrica*, 49(4):1057-1072.

Engle, R. F. and Granger, C. W. J. (1987), "Cointegration and Error Correction: Representation, Estimation, and Testing", *Econometrica,* 55(2): 251-276.

Gulati, A. and Kelley, T. (1999), *Trade Liberalization and Indian Agriculture,* London: Oxford

University Press.

Hallam, D. and Zanoli, R. (1993), "Error Correction Models and Agricultural Supply Response", *European Review of Agricultural Economics*, 20(2):151-166.

Hwang, J. (2002), "The Demand for Money in Korea: Evidence from the Cointegration Test", *International Advances in Economic Research*, 8(3):188-195.

Indiradevi, P., Thomas, E.K. and Thomas, J. K. (1990), "Growth and Supply Response of Banana in Kerala," *Agricultural Situation in India*, 45 (4): 239-242.

Johansen, S. (1988), "Statistical Analysis of Cointegration Vectors", *Journal of Economic Dynamics and Control*, 12(2-3):231-254.

Johansen, S. and Juselius, K. (1990), "Maximum Likelihood Estimation and Inference on Cointegration with Application to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, 52(2):169-210.

Johansen, S. and Juselius, K. (1992), "Testing Structural Hypotheses in a Multivariate Cointegration Analysis of the PPP and the UIP for UK," *Journal of Econometrics*, 53 (1-3):211-244.

Just, R. E. (1993), "Discovering Production and Supply Relationships: Present Status and Future Opportunities," *Review of Marketing and Agricultural Economics,* 61(1): 11- 40.

Kanwar, S. (2004), "Price Incentives, Non-price Factors and Crop Supply Response: The Indian Cash Crops," Working Paper No. 132, Centre for Development Economics, Delhi School of Economics, India, November.

Krishna, R. (1963), "Farm Supply Response in India-Pakistan: A Case Study of the Punjab Region", *The Economic Journal,* 73(291): 477-487.

Kumar, P. and Rosegrant, M. (1997), "Dynamic Supply Response of Cereals and Supply Projections: A 2020 Vision," *Agricultural Economics Research Review*, 10(1): 1-22.

Lahiri, A. K. and Roy, P. (1985), "Rainfall and Supply Response: A Study of Rice in India", *Journal of Development Economics*, 18(2-3): 315-334.

Lenka, J. (2010), Crop Diversification in Orissa: An Econometric Analysis, in Lenka, J. (ed) *Current Issues in Indian Agriculture,* New Delhi: Serials Publication.

McKay, A., Mossissey, O. and Vaillant, C. (1998), "Aggregate Export and Food Crop Supply Response in Tanzania: DFID-TREP, Credit Discussion Paper-98/4, Department of Economics, University of Nottingham, UK.

Mishra, V.N. (1998), "Economic Reforms, Terms of Trade, Supply and Private Investment in Agriculture: Indian Experience", *Economic and Political Weekly*, 33(31):2105-2109.

Moula, L. E. (2010), "Response of Rice Yields in Cameroon: Implications for Agricultural Price Policy", *Libyan Agriculture Research Center Journal International*, 1(3): 182-194.

Mythili, G. (2008), "Acreage and Yield Response for Major Crops in the Pre-and Post-reform Periods in India: A Dynamic Panel Data Approach", PP Series 061, Indira Gandhi Institute of Development of Research, Mumbai, India.

Narayana, N.S.S. and Parikh, K. S. (1981), "Estimation of Farm Supply Response and Acreage Allocation: A Case Study of Indian Agriculture," Research Report No. 81-1, International Institute for Applied Systems Analysis, Luxemburg, Austria.

Nerlove, M. (1958), "Distributed Lags and Estimation of Long-run Supply and Demand Elasticities: Theoretical Considerations", *Journal of Farm Economics*, 40(2): 301-311.

Oury, B. (1965), "Allowing for Weather in Crop Production Model Building", *Journal of Farm Economics*, 47(2): 270-283.

Palanivel, T. (1995), "Aggregate Agricultural Supply Response in Indian Agriculture: Some Empirical Evidence and Policy Implementation", *Indian Economic Review*, 30 (2): 251-263.

Paltasingh, K. R., Goyari, P. and Mishra, R. K. (2012), "Measuring Weather Impact on Crop Yield using Aridity Index: Evidence from Odisha", *Agricultural Economics Research Review*, 25(2): 205-216.

Rao, N.C. (2004), "Aggregate Agricultural Supply Response in Andhra Pradesh", *Indian Journal of Agricultural Economics*, 59(1):91-104.

Sadoulet, E. and de Janvry, A. (1995), *Qualitative Development Policy Analysis*, Baltimore, Md.: John Hopkins University Press.

Townsend, R. and Thirtle, C. (1995), "Dynamic Acreage Response: An Error Correction Model for Maize and Tobacco in Zimbabwe", University of Reading, Discussion Papers in Development Economics, Series G, 2(20).

Tripathi, A. (2008), "Estimation of Agricultural Supply Response by Co-integration Approach", Research Report, Indira Gandhi Institute of Development Research, Mumbai.

Tzouvelekas, V., Loizou, S., Giannakas, K. and Mattas, K. (2001), "Co-integration and Error-Correction Modeling of Olive Oil Consumption in Greece", *Applied Economics Letters*, 8(8): 539-543.

Yu, B., Liu, F. and You, L. (2012), "Dynamic Agricultural Supply Response under Economic Transformation: A Case Study of Henan Province, China", *American Journal of Agricultural Economics,* 94(2): 370-376.

Zhang, B. and Carter, C. A. (1997), "Reforms, the weather and productivity growth in China's grain sector," *American Journal of Agricultural Economics*, 79(4): 1266-1277.