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Food Price Inflation and the Weather God

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Abstract: This paper examines the association between the cyclical component of agricultural output and rainfall in India. Understanding this linkage is important from the perspective of formulating demand management policies. When food inflation is caused by a shortage of agricultural output resulting from inadequate rainfall and poor irrigation facilities, then a contractionary monetary policy may lead to stagflation. Considering agricultural output and rainfall data from four different states in India we find evidence in favor of association between the cyclical component of agricultural output and rainfall data.

Keywords: Agriculture output, Beveridge-Nelson Decomposition, Inflation, Rainfall, India

JEL Classification Number: C50, E31, E32.

I. Introduction

Whenever we talk about demand management policy, that is, fiscal and monetary policy, we are basically focusing on how to minimize output fluctuation around its trend (potential) level. The trend level of output is generally driven by supply side factors such as labor, human and physical capital, technology, and organization. Since technology and other factor endowments do not change in the short-run, the empirical literature takes the trend level of output (also known as the permanent component) as given. Therefore, output fluctuation (also known as the cyclical component) basically refers to fluctuation around the trend level, and is caused by the changes in the demand side components of output, and supply side shocks.[1] And, this difference between the trend and the cyclical component of output is known as the output gap.

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[1] The two main theories explaining cyclical fluctuation are Keynesian Animal Spirit Hypothesis, and Business Cycle Hypothesis. The former hypothesize that economic agents are like animals, all of a sudden becoming optimistic or pessimistic about future, thereby leading to fluctuation in aggregate demand. The latter hypothesizes that economic agents respond to positive (negative) technological shocks by supplying more (less) labors, thereby contributing to fluctuation in aggregate demand.

From the policy perspective managing the output gap is important. This is because inflation (when the cyclical component is higher than the trend component) and unemployment (when the cyclical component is lesser than the trend component) are not desirable. In addition, large fluctuations in output for a particular sector with huge employment potential such as agriculture in the case of India, will have an adverse effect on income distribution.

During the fiscal year 2010-2011, the contribution of the agricultural and agriculture related informal sector was 14 per cent of the Gross Domestic Product (GDP) and it supported livelihood of around 58 per cent of the population. Whereas, the services sector that contributed to 55 per cent of the GDP has supported livelihood of 22 per cent of the population (Central Statistical Organization, Government of India, 2012). Unequal income distribution arises as services sector requires relatively high-skilled type labors relative to low-skilled type labors in the agricultural sector. Also, fluctuation in agricultural output is much higher in comparison to the industrial and services sector. Considering the agricultural, manufacturing and services output data from Central Statistical Organization, Government of India, 2012, we find that during the period between 1991-1992 and 2009-2010,[2] the coefficient of variation for agricultural output is 191.34, in comparison to 50.48 for industry, and 22.03 for services sector.

Hence, there is a need to understand the source of cyclical fluctuation in agricultural output, and formulate policies that aim at reducing this fluctuation. Findings suggest that supply-side shocks play a predominant role in driving business cycles in developing countries (Agenor et al. 1999). In this paper, we examine the source of fluctuation in agricultural output.

To minimize cyclical fluctuation policy makers can use contractionary demand management policy (monetary policy) provided the cause of cyclical fluctuation is because of higher demand resulting from increase in consumption, investment, and government expenditures. For instance, the economic expansion of India during 2005 that has lasted until the early part of 2007 was mainly because of increase in consumption expenditure. The tighter credit policy of April 2007 was influential in reducing inflation rates from 6.7 per cent to 3.5 per cent within the next four months (Reserve Bank Bulletin, 2008).

However, the central bank may not be able to control inflation if its causes are supply-side factors. The supply of agricultural output in India can fall because of drought (especially, because 55 per cent of agricultural produce depends upon rainfall) and capacity constraint (lack of availability of physical infrastructure leading to inefficient supply chain

[2] Year refers to the fiscal year, starting from April for any particular year and ending on March, next year.

management). The agricultural sector growth rate has fallen from 7 per cent in 2010-2011 to 2.5 per cent in 2011-2012 (Planning Commission, Government of India, 2012). This may explain the high food price inflation of around 9 per cent during the last quarter of 2011-2012. Working with Whole Sale Price Index data between 1990-1991 and 2010-2011 Mishra and Roy (2011) find evidence of co-movement between food inflation and overall inflation.

Recent Wholesale Price Index data 2012, with 2004-2005 as base year reveals that food items have a total weight of 24.3 per cent – 14.3 per cent for ‘primary’ items such as cereals (4 per cent); eggs, meat and fish (2.4 per cent); and milk (3.3 per cent); and 10 per cent for manufactured food items (Ministry of Commerce and Industry, Government of India).[3] These items are price inelastic, and to some extent income inelastic.[4] However, consumption of food-items cannot move beyond steady-state level of consumption. Sustained increase in food price is more likely to happen because of supply shortage, which by lowering the trend component can lead to increase in agricultural output gap. Hence, it is expected that rainfall will have an effect on the cyclical component of agricultural output.

In this paper we look at the effect of rainfall on the cyclical component of agriculture output. To our knowledge, this study is the first of its kind done in the Indian context. The rest of the paper is organized as follows. Section 2 deals with methodology and data. Section 3 contains results. And we conclude in section 4.

2. Methodology and Data

In the 1970s, the most popular method for determining fluctuation in output was to model a time series as having a trend as a deterministic function of time. In modeling GDP, the simple model containing a linear time trend is given as follows:

$$y_t = \alpha + \beta t + \varepsilon_t \tag{1}$$

where y_t is GDP, *t* stands for time trend, ε_t has zero mean, variance σ^2, and is serially uncorrelated. But when the time series has a stochastic trend, the conventional regression analysis containing a linear trend in the model could give misleading results (Nelson and Plosser 1982; Stock and Watson 1988). Box and Jenkins (1976) allowed the trend to be driven by cumulative effects of random shocks, resulting in stochastic trend.

[3] Available at: http://eaindustry.nic.in/Download_Data_0405.html. Accessed on 12/08/2012.
[4] A rise in income will result in an increase consumption of livestock products such as meat, fish, eggs, milk, and other milk products. See, Gandhi and Zhou (2010).

Once the model is estimated using Box-Jenkins methodology, the next step is to extract the stochastic trend from the model. To estimate stochastic trend we use the Beveridge-Nelson methodology. Beveridge and Nelson (1981) show that any ARIMA model can be represented as a stochastic trend plus a stationary component where a stochastic trend is defined to be random walk, possibly with a drift.[5] For any data generating process $\{y_t\}$, using the Beveridge-Nelson methodology, we can decompose it as follows:

Let us take a general ARIMA (*p,1,q*) process, where $\{y_t\}$ is I(1) meaning $\{\Delta y_t\}$ is I(0). Here $\Delta y_t = y_t - y_{t-1}$. An ARMA (*p,q*) process of $\{\Delta y_t\}$ include both autoregressive and moving average terms i.e.:

$$\Delta y_t = f + \phi_1 \Delta y_{t-1} + \cdots + \phi_p \Delta y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$
$$\Delta y_t - \phi_1 \Delta y_{t-1} - \cdots - \phi_p \Delta y_{t-p} = f + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

In lag operator form:

$$\Delta y_t - \phi_1 L \Delta y_t - \cdots - \phi_p L^p \Delta y_{t-p} = f + \varepsilon_t + \theta_1 L \varepsilon_t + \cdots + \theta_q L^q \varepsilon_{t-q}$$
$$(1 - \phi_1 L - \cdots - \phi_p L^p) \Delta y_t = f + (1 + \theta_1 L + \cdots + \theta_q L^q) \varepsilon_t \quad (2)$$
$$\phi(L) \Delta y_t = f + \theta(L) \varepsilon_t$$

provided the roots of $1 - \phi_1 L - \cdots - \phi_p L^p = 0$ lie outside the unit circle, both sides of (2) can be divided by $(1 - \phi_1 L - \cdots - \phi_p L^p)$ or $\phi(L)$ to obtain:

$$\Delta y_t = \mu + (1 + \theta_1 L + \cdots + \theta_q L^q) \varepsilon_t \Big/ (1 - \phi_1 L - \cdots - \phi_p L^p)$$
$$\Delta y_t = \theta(L) \varepsilon_t / \phi(L)$$
$$\Delta y_t = \psi(L) \varepsilon_t$$

where $\sum_{j=0}^{\infty} \left| \psi_j \right| < \infty$, $\mu = f \Big/ (1 - \phi_1 L - \cdots - \phi_p L^p)$ and

$$\psi(L) = (1 + \theta_1 L + \cdots + \theta_q L^q) \Big/ (1 - \phi_1 L - \cdots - \phi_p L^p).$$

By rewriting, $\Delta y_t = \psi(L) \varepsilon_t$, we get: $y_t = \mu + y_{t-1} + \psi(L) \varepsilon_t$

To solve the above difference equation we have to recursively substitute lagged y_t. By assuming $y_0 = 0$ and $\varepsilon_r = 0$ for $r \le 0$, the solution to the above difference equation is given as:

[5] As state-wise employment data are not available for the period considered, we do not use the Blanchard and Quah (1989) decomposition technique.

$$y_t = \mu t + h\sum_{r=1}^{t}\varepsilon_r + d(L)\varepsilon_t \tag{3}$$

where $h = \sum_{j=0}^{\infty} c_j \Rightarrow h = \dfrac{\sum_{j=0}^{q}\theta_j}{\sum_{i=0}^{p}\phi_i}$ and $d_i = -\sum_{j=i+1}^{\infty}\psi_j$

We can write equation 3 as: $y_t = y_t^p + y_t^s$ (4)

where $y_t^p = \mu t + h\sum_{r=1}^{t}\varepsilon_r$ and $y_t^s = d(L)\varepsilon_t$

or $y_t^p = \mu + y_{t-1}^p + h\varepsilon_t$

$$y_t = y_t^p + y_t^s$$

where $y_t^p = \mu t + h\sum_{r=1}^{t}\varepsilon_r$ and $y_t^s = d(L)\varepsilon_t$ or $y_t^p = \mu + y_{t-1}^p + h\varepsilon_t$

where y_t^p is the stochastic trend component. It is modeled as random walk with a drift μ. y_t^s is the cyclical component. The trend and the cyclical components of the time series are both proportional to the disturbance term ε_t, and are thus perfectly correlated. Beveridge and Nelson (1981) defined the trend (also known as the permanent component) as that part of y_t which will be continued into the future, whereas, the cyclical (also known as the temporary part) is purely a stationary random process. Once we decompose the state agricultural output data into trend and cyclical components, we regress the cyclical component on the state rainfall data with a lag.

2.1 Data

We have agricultural GDP data for four different states in India, namely, Bihar, Punjab, Uttar Pradesh, and West Bengal. As we do not have matching rainfall data for other states in India, we limit our analysis to these four states only to study the effect of rainfall on agricultural growth. The data consisted of 46 annual observations from 1960-61 to 2005-06 measured in 1993-94 prices. The data used in this study are real agricultural state GDP data measured in millions of Indian Rupees. The data are obtained from *Central Statistical Organisation (CSO)*, Government of India. Data on rainfall are sourced from Indian Institute for Tropical Meteorology, Government of India.

Table 1: Descriptive Statistics for Agricultural Gross Domestic Product

Agricultural GDP	Mean	Median	Standard Deviation	Minimum	Maximum
Bihar	68116	61679	21693	35700	143594
Punjab	74971	52303	61407	21713	253466
Uttar Pradesh	235501	213822	170415	178188	615737
West Bengal	110404	68494	103481	48540	386464

Note: Figures are in Indian Rupees Million at 1993-94 prices. *Source: CSO*.

3. Results

To undertake data decomposition first we check for data stationarity using the Augmented Dickey-Fuller (ADF) test, and find evidence of non-stationarity. Specifically, we estimated the regression model as:

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{j=1}^{n} \alpha_j \Delta y_{t-j} + \varepsilon_t ,$$

where: y_t is the logarithm of the agricultural GDP series for each state, and β_1 is the ADF parameter. To determine appropriate specification for the number of lagged GDP terms, we use the standard lag-length diagnostic tests such as the AIC and Schwarz Criterion. The most parsimonious specification is obtained choosing a lag-length of $n = 3$. The partial t-statistics on second and third-order lagged output are not statistically significant (P-value>0.10). Loss functions, such as AIC and Schwarz Criterion, are roughly minimised in the neighbourhood of $n = 3$. Given the MacKinnon's (1996) critical values of 2.61, we fail to reject the null hypothesis of a unit root at the five per cent level of significance.

Taking first difference of the data, we reject the null hypothesis of a unit root at the one per cent level of significance. The results in Table 2 show that for all the four states, data exhibit unit root, suggesting that these variables are not mean reverting but are I(1) processes. Hence, the agricultural GDP data are non-stationary. To make the data stationary, we take the first difference of the data. For our sample, we examine the autocorrelation and the partial autocorrelation function of the first difference of the log of agricultural output (y_t). They are identified, and estimated as an ARIMA process. The Beveridge-Nelson decomposition is then applied to compute the trend and the cyclical components of y_t. The results of the estimated model for each of the four states are given in Appendix.[6]

Table 2: Augmented Dickey-Fuller (ADF) Test Results

Statistic /Diagnostic	${y_t}^b$	${y_t}^p$	${y_t}^{up}$	${y_t}^{wb}$
ADF Test	1.56	2.45	0.62	1.78
AIC	21.41	21.08	25.34	22.96
Schwarz Criterian	21.43	21.43	25.42	23.17
Durbin Watson	2.12	2.17	2.14	2.12

Note: ${y_t}^b$, ${y_t}^p$ ${y_t}^{up}$ and ${y_t}^{wb}$ represent the natural logarithm of Agricultural GDP for the States of Bihar, Punjab, Uttar Pradesh and West Bengal. In absolute value and compared to the MacKinnon (1991) critical value of 2.61 for a 10 per cent level of significance.

The permanent and temporary components can now be easily calculated using the solution to the difference equations given in Appendix. For example, in the case of West Bengal the permanent component of GDP is given as $y_0 + 0.0388 \times t + 0.066 \sum_{r=1}^{t} \varepsilon_r$. " y_0 " is the log value of West Bengal's agricultural GDP for the fiscal 1960/61, and $t = 1 \cdots 46$. The permanent component of the log output for West Bengal for the year 1960/61 is given as $y_{1960/61}^{wb} + .0388 \times 1 + 0.066 \varepsilon_{1960/61}$. Similarly, the permanent component of the log output for West Bengal for the year 1961/62 is given as $y_{1960/61}^{wb} + .0388 \times 2 + 0.066(\varepsilon_{1960/61} + \varepsilon_{1961/62})$. Repeating for each point in the data sets for West Bengal, starting from 1960/61 and ending 2005/06, will yield the trend component. We follow the same rule in calculating the trend components of GDP for other states. In case of Uttar Pradesh and Bihar, involving an *AR (1)* process, we lose two initial observations (one was due to differencing the data and the other was related to the *AR(1)* process). Likewise, in the case of Punjab, 6 initial observations are lost.

Once we estimated the trend component we can easily calculate the cyclical component by subtracting the trend component from the actual data sets. Given that the GDP series for each state is expressed as natural log units, the trend and cyclical components of GDP are also in natural log format. In the final step, we test for association between the cyclical component of agricultural GDP and rainfall. Agricultural output will increase in the event of normal rainfall, and will fall in the event of sub-optimal rainfall. This is particularly true

[6] Estimation was performed using the econometric software package Eviews 6.

if there is lack of physical infrastructure – making rainfall the sole driver for agricultural growth.

For estimation, we use Ordinary Least Square (OLS). The dependent variable is the cyclical component of state agricultural GDP, and the independent variable is rainfall. As heavy rainfall (flood) without proper irrigation facilities may harm crop production (some crops cannot withstand water stagnation) we take into consideration rainfall square as an additional explanatory variable. We estimate:

$$y_j^{tt} = \beta_0 + \beta_1 r_{j-1}^t + \beta_2 r_{j-1}^{2t} + e_j^t$$

where, y_j^{tt} represents the cyclical component of the agriculture GDP for the state *j* (*j* = Bihar, Punjab, Uttar Pradesh and West Bengal) at time period *t*. For the crops grown in these states, harvest time typically happens during February-March of every year. Therefore, we have taken the lag value for rainfall. That is, the effect of last fiscal year rainfall is expected to have an impact on the current year's harvest. All the variables are expressed in log form. The results are as follows:

Table 3: Effects of Rainfall on the Cyclical Component of Agriculture

Cyclical Component y_j^{tt}	Constant β_0	Independent Variables	
		β_1 (Rainfall)	β_2 (Heavy Rainfall)
Bihar	6.689	0.216*	0.322***
Model diagnostics: Adj. R^2 = 0.566			
Punjab	8.556*	0.4112	0.788
Model diagnostics: Adj. R^2 = 0.163			
Uttar Pradesh	0.566	0.1002*	-0.0741**
Model diagnostics: Adj. R^2 = 0.623			
West Bengal	3.822***	0.1855*	0.652
Model diagnostics: Adj. R^2 = 0.486			

Note: * Indicates significance at 1per cent level; ** Indicates significance at 5per cent level; *** Indicates significance at 10per cent level. Standard errors are in parenthesis.

From the results, we find evidence about rainfall affecting the cyclical component of agricultural GDP. The results are particularly robust for the states of Bihar, Uttar Pradesh, and West Bengal (significant β_1s). Interestingly, excessive rainfall has not affected agricultural output in Bihar (significant positive β_2). The case is opposite for Uttar Pradesh, where excessive rainfall has affected crop output (significant negative β_2). This may be because of the crops grown in Bihar are more hardy such as jowar, bajra, etc., as compared to crops like, rice, wheat, sugarcane etc., grown in Uttar Pradesh, which are adversely affected by water stagnation.

As the model is in log format, the results indicate for a hundred per cent increase in rainfall the cyclical component of agricultural output has risen by 24 per cent for Bihar, 10 per cent for Uttar Pradesh, and 20 per cent for West Bengal. However, we did not get any statistically significant results for the State of Punjab. One possible reason is that Punjab has relatively developed agricultural infrastructure in comparison to the other three states. In general, rainfall seems to be predominant driver of growth for agricultural output in Bihar, Uttar Pradesh and West Bengal.

4. Conclusion

This paper suggests that fluctuation of agricultural GDP in three major states in India is due to the supply-side shock rather than caused by the demand-side factors. For the State of Punjab we did not find any statistically significant relation between the cyclical component of agricultural output and rainfall. Our results suggest that whenever we see a rise in food prices, it is basically because of shortage caused by bad harvest rather than increase in aggregate demand. Supply shortage resulting from inadequate rainfall lower the trend component of agricultural output, and increase the agricultural output gap. Contractionary monetary policy will not be successful as it is the rainfall which is an important factor that affects the food price inflation. What is required is the use of supply management policies like investment in suitable infrastructure, focusing on developing new technology, efficient supply chain management, etc to ease food price inflation.

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Appendix

Bihar: *Identification*: $\Delta y_t = \underset{(0.0087)}{0.0077} - \underset{(0.129)}{0.632}\,\Delta y_{t-1} - \underset{(0.00003)}{0.0797}\,\varepsilon_{t-1} - \underset{(0.086)}{0.792}\,\varepsilon_{t-12} + \varepsilon_t$

Solution: $y_t = y_0 + 0.0047t + 0.0785\sum_{r=1}^{t}\varepsilon_r + 0.049\varepsilon_t + 0.486(\varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2} + \cdots + \varepsilon_{t-11})$

Punjab: *Identification*: $\Delta y_t = \underset{(0.0073)}{0.039} - \underset{(0.107)}{0.679}\,\Delta y_{t-5} - \underset{(0.057)}{0.869}\,\varepsilon_{t-5} + \varepsilon_t$

Solution: $y_t = y_0 + 0.023 \cdot t + 1.113\sum_{r=1}^{t}\varepsilon_r - 0.518 \cdot (\varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2} + \varepsilon_{t-3})$

Uttar Pradesh: *Identification*: $\Delta y_t = \underset{(0.0012)}{0.028} + \underset{(0.029)}{0.0448}\,\Delta y_{t\text{-}1} - \underset{(0.0391)}{0.0597}\,\Delta y_{t\text{-}1} - \underset{(0.025)}{0.96}\,\varepsilon_{t\text{-}1} + \varepsilon_t$

Solution: $y_t = y_0 + 0.027 \cdot t + 0.0393\sum_{r=1}^{t}\varepsilon_r + 0.946 \cdot \varepsilon_t$

West Bengal: *Identification*: $\Delta y_t = \underset{(0.0092)}{0.0388} - \underset{(0.0408)}{0.934}\,\varepsilon_{t-15} + \varepsilon_t$

Solution $y_t = y_0 + 0.0388t + 0.066\sum_{r=1}^{t}\varepsilon_r + 0.934(\varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2} + \cdots + \varepsilon_{t-14})$

Note: Standard errors are in parenthesis.