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The Curious Case of Indian Agriculture

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Abstract: This paper examines association between the cyclical component of agricultural output and rainfall in India. When the cause of food inflation is because of supply shortage driven by inadequate rainfall and poor irrigation facilities, then a contractionary monetary policy may lead to stagflation. Considering agricultural output and rainfall data from four states in India we find evidence in favor of association.

Key Words: Agriculture output, Beveridge-Nelson Decomposition, Rainfall, India.

JEL Classification: C50, E31, E32.

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1. Introduction

Whenever we talk about demand management policy, that is, fiscal, and/or monetary policy, we are basically focusing on how to minimize fluctuation in output around the the trend or potential level. The potential (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 consider the trend level of output (also known as permanent component) as given. Therefore, output fluctuation basically refers to fluctuation around the trend level, and is cause by the changes in the demand side components of output (also known as the cyclical component).[3] And, the difference between trend and the cyclical component of output is known as output gap.

From the policy perspective managing output gap is important. This is because too much inflation (occurs when cyclical component is more than the trend component), or too many unemployment (occurs when cyclical component is less than the trend component) is not desirable. In addition, big fluctuation in output concerning a particular sector with huge employment potential such as agriculture in case of India, will affect overall growth, and have an adverse effect on income distribution.

In 2010/11, agricultural and agriculture related informal sector supported livelihood of around 58 per cent of the population, whereas contributing only around 14 per cent to Gross Domestic Product (GDP). Much of the increase in income inequality is on account of the poor being dependent on agriculture. Also, fluctuation in agricultural output is much higher as compared to that in industrial and services sector. During the period 1991/92 to 2009/10, the coefficient of variation for agricultural output is 191.34, in comparison to 50.48 for industry, and 22.03 for services sector (Central Statistical Organisation, Government of India, 2012).

Hence, there is a need to understand source of cyclical fluctuation in agricultural output, and formulate policies that aims 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, and policy choice available to minimize this fluctuation.

About effective policy choice, it depends on whether fluctuation in agricultural output is demand or supply driven. If the cyclical fluctuation in output is largely driven by supply side factors then demand management policies will be less useful in minimizing fluctuation. On the contrary, if the cyclical component of the output is not driven by supply side factors then it indicate that the economy is well endowed with factors such as irrigation, weather insurance, etc that reduces supply side shocks. The reason for cyclical fluctuation then is because of changes in demand side factors such as, consumption expenditure, government expenditure, investment expenditure, and net exports. Under such circumstance, demand management policies will be efficient to stabilize the output around its potential level.

[3] 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 hypothesize that economic agents respond to positive (negative) technological shocks by supplying more (less) labors, thereby contributing to fluctuation in aggregate demand.

When the Reserve Bank of India (RBI) – the Indian Central Bank – raises interest rates (repo and reverse repo rates), it is seen as an attempt to bring down inflation by trying to control the demand-side factors. A higher interest rate, which most often translates into higher loan rates, can control consumption expenditures (contributing close to around 68 per cent of economy-wide demand in 2010/11), and by raising the cost of capital, can also bring down investment expenditure. For example, 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 around 6.7 per cent to around 3.5 per cent within a quarter.

But what happens if the cause of inflation is because of supply-side factors. Supply of output can get affected because of drought (especially when around 55 per cent of agricultural produce in India depends upon rainfall) and capacity constraint (lack of availability of physical infrastructure). Agricultural sector growth rate has fallen from 7 per cent in 2010/11 to 2.5 per cent in 2011/12 (Planning Commission, Government of India, 2012). This may explain the high food price inflation of around 9 per cent during last quarter of 2011/12.

Therefore, it is important to understand the source of cyclical fluctuation. If there is evidence about association between cyclical component of agricultural output and rainfall, then we interpret a good (bad) harvest is a function of good (bad) rainfall. Rise (fall) in food price, is basically because of shortage (glut) caused by bad (good) harvest rather than cause by an increase (decrease) in aggregate demand. Under such instance, when cause of inflation is because of supply shortage, a contractionary monetary policy may lead to stagflation. On the other hand, if there is no evidence about association between cyclical component of agricultural output and rainfall, then we interpret the price rise in agricultural output is driven solely because of demand side factors, and there is a need to follow a contractionary demand management policy. 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 used for this study. 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:

$$y_t = \alpha + \beta t + \varepsilon_t \qquad (1)$$

where y_t is GDP, t stands for time trend, ε_t has zero mean, variance σ^2, and is serially uncorrelated. The idea behind this specification is that the potential output is measured along the trend line, and the residuals measure cyclical fluctuations around the trend output. The main drawback of this type of model is that the trend is assumed to be a deterministic function of time. But the trend itself may vary over time.

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 trend to be driven by cumulative effects of random shocks, resulting in stochastic trend. The advantage of using Box-Jenkins framework is that "they have the potential to approximate dynamics more parsimoniously than purely autoregressive or moving average models" (Diebold 1998, p. 180).

Once the model is estimated using Box-Jenkins methodology, the next step is to extract the stochastic trend from the model. Mechanical filters, such as the Hodrick and Prescott (1997) filter, hereafter the HP filter, or the band-pass filter proposed by Baxter and King (1995), hereafter the BK filter, can extract a trend measure from the actual output series. However, these univariate filters have some drawbacks. For example, Harvey and Jaeger (1993) find that the HP filter with (nearly) integrated data can induce spurious cyclicity. Guay and St-Amant (1996) show that both the BK and HP filters do not accurately decompose time series into their trend and cyclical components when the data have the typical spectral (or pseudo-spectral) shape identified by Granger (1996). Moreover, Baxter and King (1995) find that the HP and the BK filters show instability of estimates near the end of the sample period.

In this paper an alternative estimation techniques, the Beveridge-Nelson (1981) methodology is used to estimate the stochastic trend. Beveridge and Nelson 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.[4] For any data generating process y_t, using Beveridge-Nelson methodology, we can decompose it as follows:

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

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

or $y_t^p = \mu + y_{t-1}^p + h\varepsilon_t$ (2)

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 permanent component) as that part of y_t which will be continued into the future, whereas, the cyclical (also known as temporary part) is purely a stationary random process. Once we decompose the state agricultural output data into trend and cyclical component, we regress the cyclical component against the state rainfall data.

Data

We have agricultural GDP data for four 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 to study the effect of rainfall on agricultural growth. In terms of availability of physical infrastructure, and agro-climatic condition there is not much variation across various Indian states. Hence, the result from this exercise is expected to hold true for other Indian states, as well. The data consisted of

[4] We do not use Blanchard and Quah (1989) decomposition technique, as state-wise employment data are not available for the concerned time period.

46 annual observations from 1960/61 to 2005/06 measured at 1993-94 prices. The data used in this study are real agricultural state GDP data measured in Indian Rupees. The data is obtained from *Central Statistical Organisation (CSO)*, Ministry of Statistics and Programme Implementation, Government of India. Data on rainfall are sourced from Indian Institute for Tropical Meteorology, Government of India.
(INSERT TABLE 1)

3. Results

To undertake data decomposition first we will have to check for data stationarity. To test for non-stationarity, we use Augmented Dickey-Fuller (ADF) test. We find evidence of non-stationarity. 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. 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 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.
(INSERT TABLE 2)

Taking first difference of the data, we reject the null hypothesis of a unit root at the one per cent level of significance. Hence, the agricultural GDP data are non-stationary. To convert the data into 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 and Nelson (1981) 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 Box 1.[5]

The permanent and the temporary components can now be easily calculated using the solution to the difference equations given in Box 1. For example, in 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 $y^{wb}_{1960/61} + .0388 \times 1 + 0.066 \varepsilon_{1960/61}$. Similarly, the permanent of the log output for

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

West Bengal for the year 1961/62 is given as $y^{wb}_{1960/61} + .0388 \times 2 + 0.066(\varepsilon_{1960/61} + \varepsilon_{1961/62})$. 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 lost two initial observations (one was due to differencing the data and the others were related to *AR(1)* process). Likewise, in case of Punjab, 6 initial observations are lost.

Once we estimated the trend component we can easily calculate the cyclical component by subtracting trend component from the actual data sets. Given that the GDP series for each state is expressed in natural log, the trend and cyclical components of GDP are also in natural log format.

In the final step, we test for association among the cyclical component of agricultural GDP with rainfall. The idea is: agricultural output will increase in the event of normal rainfall, and will fall in the event of sub-optimal rainfall. This will be particularly true 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 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. To be precise, we estimate the following equation:

$$y^{tt}_{j} = \beta_0 + \beta_1 \overset{t}{r}_{j\text{-}1} + \beta_2 \overset{2t}{r}_{j\text{-}1} + e^{t}_{j}$$

where, y^{tt}_{j} represents cyclical component of the agriculture GDP for 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 lag value for rainfall. That is, the effect of last fiscal year rainfall is expected to have impact on current year's harvest. All the variables are expressed in log form. The results are as follows:

(INSERT TABLE 3)

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 and Uttar Pradesh. This is also congruent with the fact that these two states lack basic irrigation facilities. The agricultural outputs in these states are dependent upon rainfall relative to other two states. Interestingly, too much rainfall seems to have not affected agricultural output in Bihar. The case is opposite for Uttar Pradesh, where, too much rainfall seems to have affected crop output. This may be because of the crops grown in Bihar are more hardy type crops 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 cyclical component of agricultural output seems to have risen by any thing between 16 per cent (for Bihar), and 7 per cent (for Uttar Pradesh). We however did not get any statistically significant results for the State of Punjab. One possible reason is Punjab have much developed agricultural infrastructure in comparison to these other three states. Accordingly, rainfall seems to have less effect on the cyclical component of agricultural output in Punjab. In general, rainfall seems to be predominant driver of growth for agricultural output in Uttar Pradesh and West Bengal.

4. Conclusion

This paper suggest that cyclical component of agricultural GDP in India is more responsive to supply-side shock rather than demand-side shock. That is, whenever we see rise in food prices, it is basically because of shortage cause by bad harvest rather than increase in aggregate demand. Understanding the sources of cyclical fluctuation in output and its implications on other key macroeconomic variables are very crucial in identifying the right choice of policy measures that aim at reaching higher growth trajectory and minimize inflationary pressure. When output fluctuation is because of supply side shocks resulting from unfavorable weather condition then demand management policy measures will be less useful in stabilizing the output around its trend level. What is required is the use of supply management policies like investment in suitable infrastructure, focusing on developing new technology, maintaining buffer stock of essential commodities, etc. Such attempts will ensure stability of growth, especially in the agricultural sector in India.

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Table 1: Descriptive Statistics for Agricultural Gross Domestic Product

Agricultural GDP[!]	Mean	Median	Standard Deviation	Maximum	Minimum
Bihar	6182.5	6082	1019.7	8298	3570
Punjab	5562.1	4964.9	2553.7	10072	2171
Uttar Pradesh	32826.0	31762.1	10843.6	51268	17818
West Bengal	10116.8	7778.1	4983.5	19916	4845

[!] Figures are in Indian Rupees Million at 1993-94 prices.
Source: CSO.

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

Statistic / Diagnostic	y_t^b	y_t^p	y_t^{up}	y_t^{wb}
ADF Test [a]	1.63	0.989	0.222	0.183
AIC	-1.33	-3.31	-1.91	-2.15
Schwarz Criterian	-1.20	-3.22	-1.64	-2.02
Durbin Watson	2.07	2.09	2.01	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.
[a]In absolute value and compared to the MacKinnon (1991) critical value of 2.61 for a 10 per cent level of significance.

Table 3: Results

Dependent Variable y_j^{tt}	Constant β_0	Independent Variables β_1	β_2
Bihar *Model diagnostics* Adj. $R^2 = 0.566$	6.689 (4.173)	0.216[1] (0.078)	0.322[3] (0.169)
Punjab *Model diagnostics* Adj. $R^2 = 0.163$	8.556[1] (1.221)	0.4112 (0.328)	0.788 (0.455)
Uttar Pradesh *Model diagnostics* Adj. $R^2 = 0.623$	0.566 (0.226)	0.1002[1] (0.033)	-0.0741[2] (0.0382)
West Bengal *Model diagnostics* Adj. $R^2 = 0.486$	3.822[3] (1.722)	0.1855[1] (0.097)	0.652 (0.462)

Notes: 1. Indicates significance at 1per cent level; 2. Indicates significance at 5per cent level; 3. Indicates significance at 10per cent level. Standard errors are in parenthesis.

Box1

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:

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

Punjab

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

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

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

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

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