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ROLE OF INSTITUTIONAL CREDIT IN INDIAN AGRICULTURAL PRODUCTION: A DETAILED TIME SERIES ANALYSIS

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ABSTRACT

In this paper, I look at the relation between institutional credit and agricultural production through time series analysis. This analysis gave some expected yet not so desired results. Stationarity and Co-integration, two major characteristics of time series analysis and long run relationship between variables have been checked for the chosen variables, followed by identification of the stochastic process involved in each series. The series we've chosen for analyzing the 'Effect Institutional Credit on Indian Agriculture' are the following: Production of food grain and major commercial crop in India in between 1970-2008 and Institutional credit to agricultural sector over the same time period. The empirical results suggest that Indian agriculture can improve a lot if sufficient amount of credit is issued to agricultural sector and if the issued fund is used efficiently. Farmers have to depend on non-institutional credit sources. Besides, complex credit policies have also refrained the farmers from taking a step towards institutional sources. The results also show that dependence on monsoon results in fluctuation in agricultural production, which means farmers' default rate increases in times of bad monsoon, so banks do not issue credit to them. In turn, lack of fund compels the farmers to stick to old production techniques, behavior of monsoon and non-institutional sources of credit charging high interest rates. So, productivity doesn't rise significantly.

JEL Classification: O1, O13, Q1, Q18

Keywords: Institutional credit, Agricultural production, Stationarity, Co-integration

1. INTRODUCTION

Agriculture plays a crucial role in the development of the Indian economy. A large proportion of the population in India is rural based and depends on agriculture for a living. Enhanced and stable growth of the agriculture sector is important as it plays a vital role not only in generating purchasing power among the rural population by creating on-farm and off-farm employment opportunities but also through its contribution to price stability. Credit is a crucial factor in

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agricultural production and in many cases may be a limiting factor in small holder agriculture. According to Miller (1977), credit provides the means for the temporary transfer of assets from an individual or organization to one which has not. Credit may be described as a facility extended from the lender to the borrower and is repayable at maturity, which may range from a few days to several years. For a credit transaction to be completed, the borrower must provide some evidence of debt obligation in return for the loan where the loan is based solely on good reputation, financial position of the borrower and trust. Credit can also be extended to the borrower in the form of assets possessed by the lender i.e. in cash (Miller 1977; Abayomi and Salami, 2008). A strong and efficient agricultural sector has the potential to enable a country feed its growing population, generate employment, earn foreign exchange and provide raw materials for industries. The vibrancy of the sector has a multiplier effect on any nation's socio-economic and industrial fabric, because of multifunctional nature. A number of studies such as Ansari, Gerasim and Mahdavinia (2009), and Salami, et al (2010) have documented the problems of the agricultural sector in Africa countries. Aside the problem of poor access to modern technology by the peasant farmers in the African countries, the major bane of agricultural development commonly identified by the above studies among others is low investment or finance. Credit plays a major role in the transformation of traditional agriculture into a modern largescale commercial type which enhances agricultural development. It is necessary for purchasing inputs needed for effective adoption of modem agricultural techniques. Many economists have identified the lack of basic assets major constraint to agricultural development (Abayomi and Salami, 2008). Oluwasanmi and Alao (1965) clearly stated the need for credit or the purchase of farm inputs such as improved seed varieties, breeds of livestock, fertilizers, insecticides, pesticides, modern implement, among others. They also stressed the suitability of terms of credit as a necessary condition for fostering agricultural development. Oyatoye (1981) averred that credit is a major factor necessary for technological transfer in traditional agriculture. According to her, given the availability of inputs needed to improve technology, how rapidly farmers would adopt improved technology depend on additional factors. She further identified efficient source of production credit as one of these additional factors. Oni (1987) opined that the peasant farmers do not possess enough resources to purchase these farm investments. He further stressed that it is necessary to supplement the farmer’s personal earnings to facilitate agricultural transformation. Hence the need for credit is universal. While it is needed by the less developed countries to increase productivity per farm worker and per hectare, the developed nations also need it to foster development (Jekayinfa, 1981; Abalu et al, 1981). Cole (2008) integrated theories of political budget cycles with theories of tactical electoral redistribution to test for political capture in a novel way. Studying banks in India, he found that government-owned bank lending tracks the electoral cycle, with agricultural credit increasing by 5-10 percentage points in an election year. There is significant cross-sectional targeting, with large increases in districts in

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which the election is particularly close. This targeting does not occur in non-election years, or in private bank lending. He showed that capture is costly: elections affect loan repayment, and election year credit booms do not measurably affect agricultural output. Sreeram (2007) concluded that increased supply and administered pricing of credit help in the increase in agricultural productivity and the well-being of agriculturists as credit is a sub-component of the total investments made in agriculture. He also stated that the diversity in cropping patterns, holding sizes, productivity, regional variations make it difficult to establish a causality for agriculture or rural sector. In the last five decades, the Government's objectives in agricultural policy and the instruments used to realize the objectives have changed from time to time, depending on both internal and external factors. Agricultural policies at the sectoral level can be further divided into supply side and demand side policies. The former includes those relating to land reform and land use, development and diffusion of new technologies, public investment in irrigation and rural infrastructure and agricultural price supports. The demand side policies on the other hand, include state interventions in agricultural markets as well as operation of public distribution systems. Such policies also have macro effects in terms of their impact on government budgets. Macro level policies include policies to strengthen agricultural and non-agricultural sector linkages and industrial policies that affect input supplies to agriculture and the supply of agricultural materials.

An important aspect that has emerged in last three decades is that the credit is not only obtained by the small and marginal farmers for survival but also by the large farmers for enhancing their income. But in India the overall thrust of the current policy regime assumes that credit is a critical input that affects agricultural or rural productivity and is important enough to establish causality with productivity. Therefore, in this backdrop I have undertaken the case study of determining any co-integration between the credit to agrarian sector and its production of major crops. An analysis of several sets of data for the same sequence of time periods is called multiple or multivariate time series analysis. The series chosen for analyzing the 'Effect Institutional Credit on Indian Agriculture' are the following: Production of food grain and major commercial crop in India in between 1970-2008 and Institutional credit to agricultural sector over the same time period. I wish to study the dynamics or temporal structure of the data by time series analysis. The paper is divided in 4 sections apart from introduction at the beginning. Section 2 gives a brief theoretical background and section 3 describes the fundamentals of time series analysis. Section 4 gives a brief description of the data. In section 5, I start the econometric analysis which is subdivided according to the progress of the analysis. Starting with the unit root test, followed by Correlogram analysis and stationary, identification of stochastic process and co integration analysis, section 5 ends with a summary of our findings from the econometric analysis. Section 6 concludes the analysis by explaining the economic backdrop of the findings.

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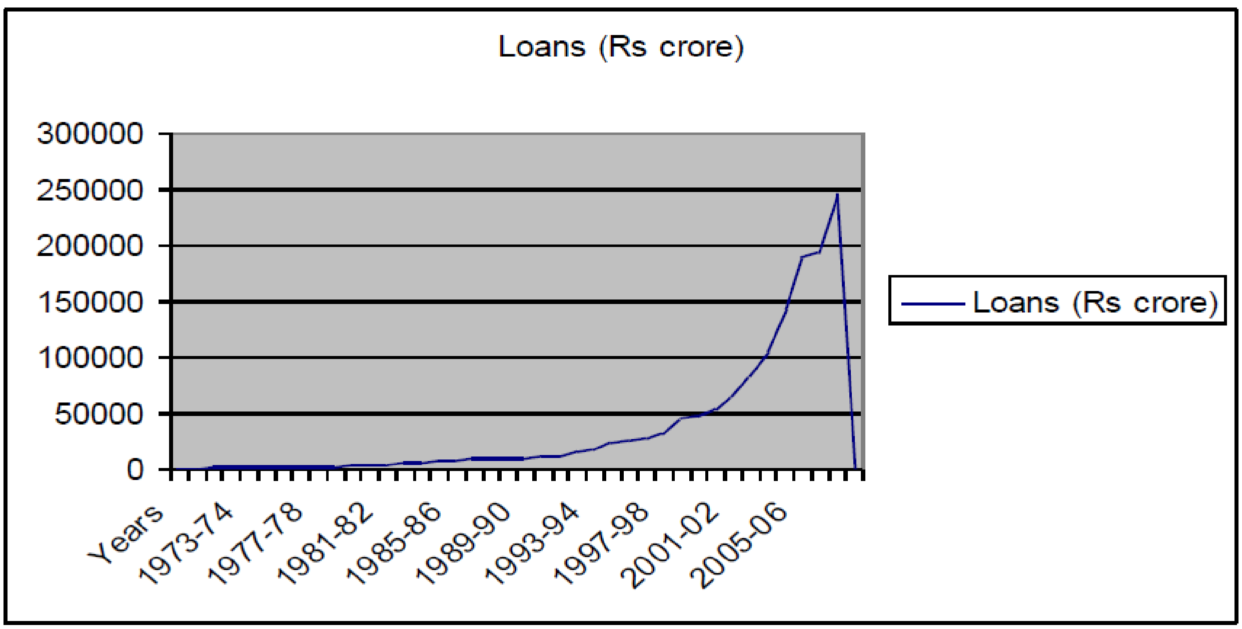
2. THEORETICAL BACKGROUND

The importance of farm credit as a critical input to agriculture is reinforced by the unique role of Indian agriculture in the macroeconomic framework and its role in poverty alleviation. Agricultural policies in India have been reviewed from time to time to maintain pace with the changing requirements of the agriculture sector, which forms an important segment of the priority sector lending of scheduled commercial banks (SCBs). In India the need for affordable, sufficient and timely supply of institutional credit to agriculture has assumed critical importance. The demand for agricultural credit arises due to i) lack of simultaneity between the realization of income and act of expenditure; ii) lumpiness of investment in fixed capital formation; and iii) stochastic surges in capital needs and saving that accompany technological innovations. Recognizing the importance of agriculture sector in India's development, the Government and the Reserve Bank of India (RBI) have played a vital role in creating a broad-based institutional framework for catering to the increasing credit requirements of the sector.

The trend in institutional agricultural credit from 1970 to 2008 is depicted in the diagram:



Three main factors that contribute to agricultural growth are increased use of agricultural inputs, technological change and technical efficiency. With savings being negligible among the small farmers, agricultural credit appears to be an essential input along with modern technology for higher productivity.

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Hence, since independence, credit has been occupying an important place in the strategy for development of agriculture. The agricultural credit system of India consists of informal and formal sources of credit supply. The informal sources include friends, relatives, commission agents, traders, private moneylenders, etc. Three major channels for disbursement of formal credit include commercial banks, cooperatives and micro-finance institutions (MFI) covering the whole length and breadth of the country. A large number of formal institutional agencies like Co-operatives, Regional Rural Banks (RRBs), Scheduled Commercial Banks (SCBs), Non– Banking Financial Institutions (NBFIs), and Self-help Groups (SHGs), etc. are involved in meeting the short- and long-term needs of the farmers. Several initiatives have been taken to strengthen the institutional mechanism of rural credit system. The main objective of these initiatives was to improve farmers' access to institutional credit. The major milestones in improving the rural credit are acceptance of Rural Credit Survey Committee Report (1954), nationalization of major commercial banks (1969 & 1980), establishment of RRBs (1975), establishment of National Bank for Agriculture and Rural Development (NABARD) (1982) and the financial sector reforms (1991 onwards), Special Agricultural Credit Plan (1994-95), launching of Kisan Credit Cards (KCCs) (1998-99), Doubling Agricultural Credit Plan within three years (2004), and Agricultural Debt Waiver and Debt Relief Scheme (2008). These initiatives had a positive impact on the flow of agricultural credit.

During the pre-green revolution period, from independence to 1964-1965, the agricultural sector grew at annual average of 2.7 per cent. This period saw a major policy thrust towards land reform and the development of irrigation. With the green revolution period from the mid-1960s to 1991, the agricultural sector grew at 3.2 per cent during 1965-1966 to 1975-1976, and at 3.1 per cent during 1976-1977 to 1991-1992. Acharya (1998) explains that the policy package for this period was substantial and consisted of: a) introduction of high-yielding varieties of wheat and rice by strengthening agricultural research and extension services, b) measures to increase the supply of agricultural inputs such as chemical fertilizers and pesticides, c) expansion of major and minor irrigation facilities, d) announcement of minimum support prices for major crops, government procurement of cereals for building buffer stocks and to meet public distribution needs, and e) the provision of agricultural credit on a priority basis. This period also witnessed a number of market intervention measures by the central and state Governments. The promotional measures relate to the development and regulation of primary markets in the nature of physical and institutional infrastructure at the first contact point for farmers to sell their surplus products.

Growth in the agriculture sector may well be judged by the increase in agricultural production over time. In economic terms, relative changes in prices of different crops also may effect substitution. In the Indian context, rice, wheat, cereals and pulses are the major food crops.

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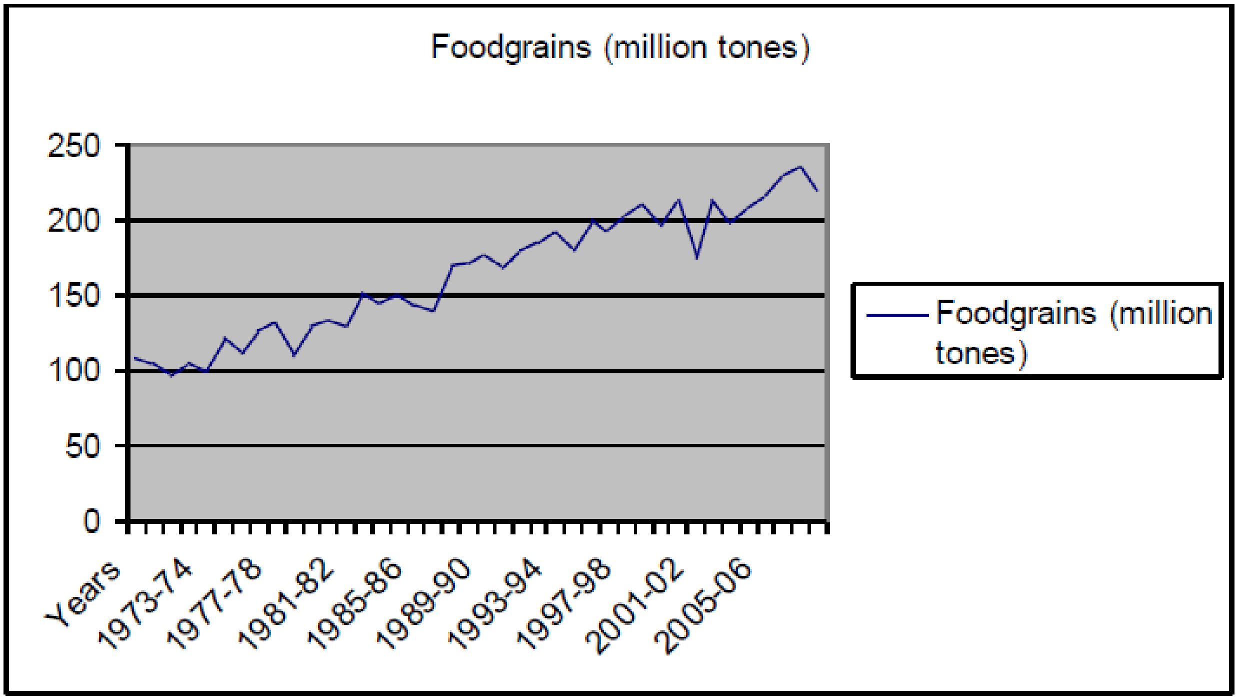
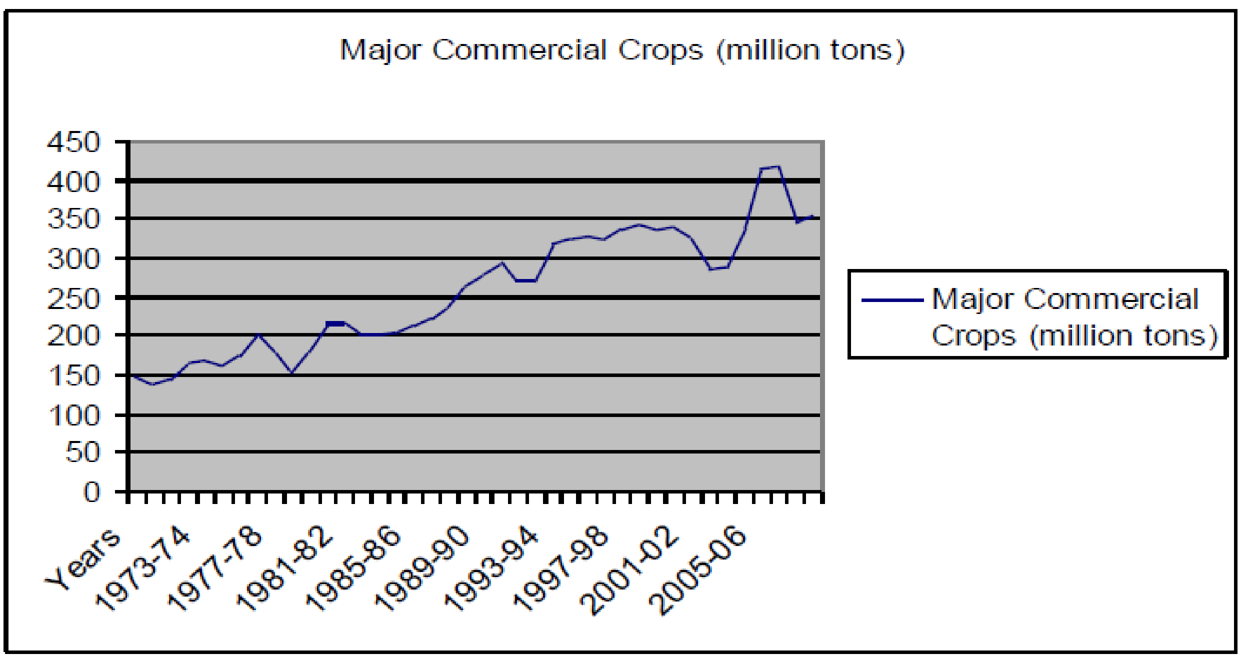
Oilseeds, sugarcane, cotton, jute & tobacco are the major cash crops. From 1970 to 2009 the overall trend in these food crops and cash crops are captured in the following diagram.





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3. TIME SERIES ANALYSIS

A time series is a sequence of data points, measured typically at successive points in time spaced at uniform time intervals. A time series is a collection of observations of well-defined data items obtained through repeated measurements over time. In other words, it is a sequence of numerical data in which each item is associated with a particular instant in time.

An analysis of single sequence of data is called univariate time series analysis.

An analysis of several set of data for the same sequence of time periods is called multivariate time series analysis.

Time series methods can be roughly divided into 2 types of methods: frequency-domain methods and time domain methods. However, in this project our approach will only be via time-domain methods. Time series analysis techniques may further be divided into parametric and non-parametric methods. The parametric approaches assume that the underlying stationary stochastic process has a certain structure which can be described using a small number of parameters (for example, using an autoregressive or moving average model). In these approaches, the task is to estimate the parameters of the model that describes the stochastic process. By contrast, non-parametric approaches explicitly estimate the covariance or the spectrum of the process without assuming that the process has any particular structure.

Broadly speaking, there are five approaches to economic forecasting based on the time series data:

1. Exponential Smoothing Methods
2. Single Equation Regression Model
3. Simultaneous Equation Regression Models
4. Autoregressive Integrated Moving Average Models
5. Vector Auto regression

A time series is a sequence of numerical data in which each item is associated with a particular instant of time. The basic assumption of time series analysis is that it has been generated by a stochastic process, i.e., each element of the series is drawn randomly from a probability distribution. Hence, it is a collection of random variable (X_t). Such a collection ordered in time is called Stochastic Process. If it is a continuous variable, it is denoted the random variable by X(t) and if t is a discrete variable, it is denoted them by $X_{t.}$-The random variables are not independent in general. Furthermore, we have just a sample size 1 on each of the random variables. There is no way of getting another observation, so we are called a 'single realization'. The two features

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are dependence and lack of replication, compel us to specify some highly restrictive models for the statistical structure of the stochastic process.

1) Stationary:

One important class of stochastic process is that of stationary process. It guarantees that there are no fundamental changes in the structure of the process that would render prediction difficult or impossible. Corresponding to these we have the concept of stationary time series.

- **STRICT STATIONARITY:**

A time series is said to be strictly stationary if the joint distribution of any set of observations X (t_1), X (t_2),……X (t_n) is the joint distribution of X (t_1+k), X (t_2+k),…..,X (t_n+k) for all n and k. Strict stationary holds for all values for n and a constant for all t. Properties of strict stationary are:

a) The mean $\mu(t)= E(X_t)$.
b) The variance $\sigma^2 (t) = var (X_t)$.
c) The auto covariance function $y(t_1, t_2) = cov (X_{t1}, X_{t2})$.
d) When $t_1 =t_2 = t$, the autocovariance is just $\sigma^2 (t)$.

For a strictly stationary time series the distribution of X(t) is independent of t. thus it is not just the mean and variance which is constant but also all the higher order moments are independent of t. so are all the higher order moments of joint distribution of any combinations of the variables $X(t_1)$, $X(t_2)$,…..

- **WEAK STATIONARITY:**

Thus, a time series is said to be weakly stationary if its mean is constant and its auto covariance function just depends on the difference $(t_2 – t_1)$, which is called the lag. Hence, we can write the auto covariance function $y (t_1, t_2)$ as y (k) where $k= t_2 - t_1$ the lag. So, the properties of the weak stationary are:

a) The mean $\mu(t)= E(x_t)$.
b) The variance $\sigma^2 (t) = var(x_t)$.
c) The auto covariance function $y(k) = cov(X_{t1}, X_{t2})$.

Since var X(t) = var X(t+k) = σ^2 = y(0), then we have the auto correlation coefficient $\rho(k)$ at a lag k as $\rho_k = y(k)/ y(0)$. P_k is called the auto correlation function and will be abbreviated as auto correlation function. A plot of ρ (k) against k is called a correlogram.

2) Non-Stationary:

In time series analysis we do not confine ourselves to the analysis of stationary time series. In fact, most of the time series we encounter are nonstationary. A simple non-stationary time series model is $X_t = \mu_t + e_t$, where mean μ is a function of time and e is weakly stationary series. A time series is said to be nonstationary if its mean is a function of a time. So, mean is a linear or quadratic function of a t.

Suppose, a stochastic process model is: $x_t = \rho xt\text{-}1 + \mathbf{e}t$

Where, ρ is a number between (-1) and (+1) and **e**t is a sequence which is independent or uncorrelated identically distributed random variable with zero mean that is,

a) E(**e**t) =0
b) var(**e**t)=σ^2e< infinity for all t
c) cov(e_t, e_s)= 0 for s not equal to t.

Here, e_t is called white noise. Clearly a white noise process is stationary, and we will assume that the e_t are identically and independently distributed. Moreover, if reference to a distribution is necessary, we will assume that they are normally distributed. In other words, they are a Gaussian white noise process.

Four Major Stochastic Processes:

1) Auto Regressive (AR)
2) Moving Average (MA)
3) Auto Regressive Moving Average (ARMA)
4) Auto Regressive Integrated Moving Average (ARIMA)

Auto Regressive Process:

Simple representation of time series is Auto Regressive process. In statistics, an autoregressive (AR) model is a representation of a type of random process; as such, it describes certain time-varying processes in economics, etc. The autoregressive model specifies that the output variable depends linearly on its own previous values.

Usually a time series L1, x2,……, xt generation process will be unknown and even if the process is assumed to be stationary, it can have a more complicated structure than a simple autoregressive (AR) process. AR model is

$X_t = \rho x_{t-1} + e_t$

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Here, $E(x_t) = o$ for all t.

$Var(x_t) <$ infinity

Cov $(x_t, x_{t+k}) = y_k$ for all t and k.

Consequently, The autocovariance function is an important tool in describing the stochastic structure of a time series because it gives us an idea of how the members of a time series depend on one another. It depends essentially on the unit of measurement of random variables.

Consequently, the covariance between two elements X_t and X_t+K of a time series is

$Cov(x_t, x_{t+k}) = \rho^k \sigma^2 X$

This is called autocovariance because it measures the linear dependence between the members of a single time series.

The covariance of X_t and X_{t+k} does not depend on the time point T, but only on the distance the two random variables are apart in time, i.e. on K since $\sigma^2 X$ is time invariant. The autocovariance are normalised by dividing each y_k by the variance Y0, of the process to obtain the auto correlation function.

$\rho k = y_k / y_o$ where $y_0 = \sigma^2 x$

Partial autocorrelation: One way to identify the order of an adequate AR process for a set of data is to estimate process of increasing order K and test the significance of Ѳk. This coefficient is called the K th partial autocorrelation coefficient and will be denoted by Ѳkk, since it is the K th coefficient of an AR process of order K. It can be shown that for large sample size of the order of the AR is in fact q, the estimated partial autocorrelations Ѳ̂kk are approximately normally distributed with mean 0 and variance 1/T for K>q, where T is sample size. Consequently, the significance of the Ѳkk approximately 95% confidence intervals,

(Ѳ̂kk -2/t^0.5, Ѳ̂kk +2/t^0.5)

In this AR process the use of unnecessary many parameters to present the process is inefficient; the question arises whether a more parsimonious representation of this process can be found. Therefore, we will represent an alternative class of stationary stochastic process in the next section.

The estimation of AR models is straightforward. We can estimate them by ordinary least square by minimizing $\sum et^2$.

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Moving Average Process

In the previous section we encountered a process that cannot be represented well by a low order AR process. Consider an infinite AR form:

X_t=- αxt-1 - $\alpha^2 x_{t-1}$ - ....+ e_t

Here using lag operator, again e_t is white noise and IαI<1, Xt = (1-Al) e_t

A process like that, where x_t is a weighted sum of members of the white noise series, is called a moving average (MA), since the weighted sum consist only of the member of the white noise series associated with the current and more recent time point. This equation solved by number of parameters and infinite series. This process has a disadvantage which is degrees of freedom is very low. MA and AR both are same process because of stationarity. Here if the condition of the stationarity is satisfied then the data generating process is called invertible.

Given a sample we determine an adequate MA order of the generating process.

The mean is $E(x_t) = 0$

The autocovariances of the MA (p) is

$$\gamma_k = \sigma^2 \sum_{i=0}^{p-k} \alpha_i \alpha_{i+k} \quad \text{for k=0,1,2,......,p}$$

$$= 0 \quad \text{for k>p}$$

Consequently the autocorrelations are $\rho_k = \frac{\sum_{i=0}^{p-k} \alpha_i \alpha_{i+k}}{\sum_{i-0}^{p} \alpha^2}$ for k=0,1,......p

$= 0$ for k>p

To determine whether a particular ρk is nonzero, we can use the available data to compute an estimate of this autocorrelation coefficient and then set up a significance test.

A commonly used estimate for ρ_k is $r_{k=\frac{c_k}{c_0}}$

Another possible estimate for ρ_k is $\bar{r}=\frac{\bar{c}}{c}$

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The significance of the autocorrelation is often tested by checking whether the r_k or r_k are inside a range ±2/T^0.5.For large T independent of sample mean the r_k and r_k are approximately normally distributed with mean zero and variance 1/T. For large T if zero does not fall within approximately 95% confidence interval

$(r_k - 2/T^{0.5}, r_k + 2/T^{0.5})$ or $(r_k - 2/T^{0.5}, r_k + 2/T^{0.5})$

The null hypothesis $\rho_k = 0$ must be rejected at the 5% level.

Auto Regressive Moving Average and Auto Regressive Integrated Moving Average

In ARMA we consider AR and MA process both. If the autocorrelations ρk have a cut off point, that is, if they are zero for all k greater than some small number and the partial autocorrelations θkk tapper of for growing k, an MA representation is suggested. AR process is suggested when the autocorrelation tapper off and the partial autocorrelations have a cut off point.

The Autoregressive Moving Average Process of order (q,p) is

$(1-\theta 1L-\theta 2L^2-.......-\theta qL^q)\ x_t = (1+\alpha 1L+\alpha 2L^2+.......+\alpha PL^P)\ e_t$

One possibility to determine these orders is to use the estimated autocorrelations and partial autocorreletion. In this case in which the autocorrelations die out slowly, the considered process is likely to be nonstationary. Suppose that we start a process

$$Y_t = y_{t-1} + x_t \qquad (a)$$

Where x_t is a non-stationary time series with mean $\mu \neq 0$, at time t=0, with $y_0=0$ and hence, $E(y_t) = E(L1 + x_2 + ... + x_t) = t\mu$. Thu the mean fallows a linear trend and the erie is not stationary because stationary requires a constant mean.

To remove the trend we can simply difference y_t and consider

$$X_t = y_t - y_{t-1} = (1-L)y_t \qquad (b)$$

It is stationary. Because it appears that differencing is a useful tool to convert nonstationary real-life processes to stationary processes. In equation (a) x_t is an ARMA(q,p) process, then y_t is called an Autoregresive Integrated Moving Average Process which is denoted by ARIMA(q,1,p). If $x_t=(1-L)^d y_t$ is an ARMA(q,p), then y_t is an ARIMA(q,d,p) process, where d is a positive integer. A time series that is stationary after d times differencing is sometimes said to be homogeneous nonstationary of degree d.

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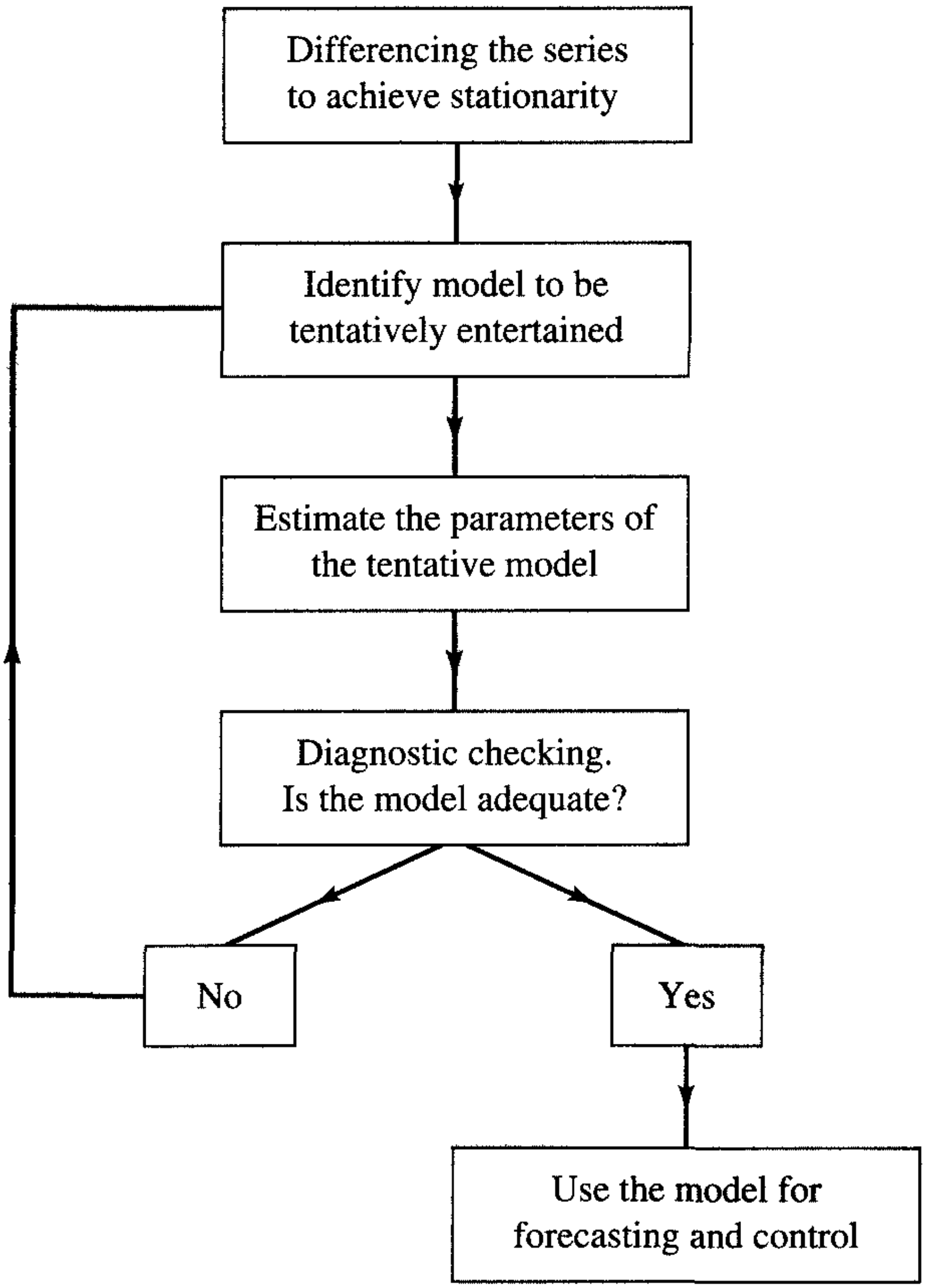
BOX JENKINS APPROACH:



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The method is partitioned into three stages:

1. IDENTIFICATION:

Identification of the most appropriate model is the most important part of the process. The first step is to determine if the variable is stationary, this can be done with the correlogram. If it is not stationary it needs to be first-differenced. (it may need to be differenced again to induce stationarity). The class of ARMA models is quite large, and in practice we must decide which of these models is most appropriate for the data at hand L1,x2…….x_n. The chief tools in identification are the autocorrelation function, the partial autocorrelation function and the resulting correlograms.

The next stage is to determine the *p* and *q* in the ARIMA (*p*, *I*, *q*) model (the *I* refers to how many times the data needs to be differenced to produce a stationary series). To determine the appropriate lag structure in the AR part of the model, the PACF or Partial correlogram is used, where the number of non-zero points of the PACF determine where the AR lags need to be included. To determine the MA lag structure, the ACF or correlogram is used, again the non-zero points suggest where the lags should be included. We first describe the correlogram, since it is conceptually the simplest. The theoretical correlogram is a plot of the theoretical autocorrelations

$\rho = \text{corr}(x_t, x_{t-k})$ against k .

1). For AR(q), the partial autocorrelation θkk will be zero for k>q and autocorrelations tapper off. Thus, for k large (say $k \geq p$), the correlogram would be expected to decline steadily. θkk is called the partial correlation between x_t and x_{t-k}.

A cutoff point of the partial autocorrelation function may be determined by comparing the estimates with ±2/^0.5T, since 1/^0.5T is the approximate standard deviation of the estimators $\hat{\theta}_{kk}$ for k>q.

2). If the series is MA(p) its theoretical correlogram would "cut off" (i.e., take the value zero) for k>p. Thus, we would expect that the sample correlogram would have a similar (though not identical) shape to the theoretical correlogram, and would therefore stay reasonably close to zero for k > p . Reversing this reasoning, we get the rule; if the correlogram seems to cut off for k > q, then the appropriate model is MA(p).

We have already seen some evidence of this: The correlogram for an MA model and the partial correlogram for an AR model both cut off. A still unanswered question is how we can identify a mixed ARMA model. In this case, it can be shown that the correlogram and partial correlogram both die down (but do not cut off). Thus, if both diagrams die down, we can conclude that the

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appropriate model is ARMA. Unfortunately, though, the diagrams do not in this case help us to decide on the order (p , q) of the mixed model.

2. ESTIMATION:

This part of the Box-Jenkins methodology is the most straightforward one. Having identified the appropriate p and q values the next stage is to estimate the parameters of the autoregressive and moving average terms. Some this calculation is done by simple least squares but sometimes it can be done by some nonlinear estimation methods. The parameters of pure AR processes can be estimated by using regression methods. It can be estimated by ordinary least square method. If MA and ARMA are involved the minimization of the sum of squared errors or the maximization of the likelihood function require nonlinear optimization methods.

3. DIAGNOSTIC CHECKING:

Once a model has been identified and estimated, it is usually taken to the the true model and forecasts can be obtained accordingly. It is virtually certain that the estimated model is not the true model. To protect against disastrous forecasting errors, the least we can do is to c heck that the fitted model is a satisfactory one. This is done by the use of diagnostic checks.

In case of Diagnostic checking there are two possibilities:

1) **Over fitting the model**: Let we have specified ARMA (q,p) then estimate either ARMA (q+1,p) or ARMA (q,p+1) or ARMA (q,+1p+1) and test the significance of extra parameters.
2) **Residual Analysis**: Compute residual sample autocorrelation r_i and compute Portmanteau Test Statistics.

A common test is the Box-Pierce test which is based on the Box-Pierce Q statistics

$$Q = n\sum_{k=1}^{h} r_k^2$$

This test was originally developed by Box and Pierce for testing the residuals from a forecast model. Any good forecast model should have forecast errors which follow a white noise model. If the series is white noise then, the Q statistic has a chi-square distribution with k-q-p degrees of freedom.If it does not follow chi- square then we need overfitting model. Then we again compute Portmanteau Test Statistics.

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UNIT ROOT TEST:

The main emphasis was on transforming the data to achieve stationarity and then estimating ARMA models. The differencing operation used to achieve a stationary involves a loss of potential information about long-run movements. The Box- Jenkins method of differencing the time series after a visual inspection of the correlogram has been formalized in the tests for unit roots. The literature on unit roots studies nonstationary which is stationary in first difference.

Consider the model,

$y_t = \alpha yt\text{-}1 + \varepsilon t$

Where, εt is white noise. In the random walk case (α=1) it is well known that the OLS estimation of this equation produces an estimate of α that is biased toward zero. However, the OLS estimate is also biased toward zero when α is less than but near to zero. Evans and Savin provide Monte Carlo evidence on the bias and the other aspects of the distributions.

To discuss the Dicky-Fuller tests, consider the model

$y_t = \beta 0 + \beta 1t + u_t$

$u_t = \alpha ut\text{-}1 + \varepsilon t$

Where, εt is a covariance stationary process with zero mean. The reduced form for this model is

$y_t = \gamma + \delta t + \alpha yt\text{-}1 + \varepsilon t$.........1

Where, $\gamma = \beta 0(1-\alpha) + \beta 1\alpha$. This equation is said to have a unit root if α=1 (in which case δ =0).

DICKEY – FULLER TEST:

The Dickey-Fuller tests are based on testing the hypothesis α=1 in equation 1 under the assumption that εt are white noise errors. There are three test statistics

$$K(1) = T(\hat{\alpha} - 1) \qquad t(1) = \frac{\hat{\alpha} - 1}{SE(\hat{\alpha})} \quad F(0,1)$$

where $\hat{\alpha}$is the OLS estimate of α in equation 1,SE ($\hat{\alpha}$) is the standard error of $\hat{\alpha}$and F(0,1) i the usual F- statistics for testing the joint hypothesis δ=0 and α=1 in equation 1.These statistics do not have the standard normal t and F distribution. The critical values for K(1) and t(1) are

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tabulated for δ=0 in Fuller and the critical values for the F(0,1) statistics are tabulated in Dickey and Fuller (1981).

THE SERIAL CORRELATION PROBLEM:

Dickey, Fuller and others developed modifications for Dickey fuller tests when e_t is not a white noise. It is called augmented Dickey Fuller test.

Augmented Dickey Fuller Test:

$$Y_t = \gamma + \delta t + \alpha y_{t-1} + \sum_{j=1}^{k} \theta_j \Delta y_{t-j} + \varepsilon_t$$

Where, Δy_{t-j} - take into account ARMA effect and T= sample size.

STATIONARY PROCESS:

Suppose we have some trend in the series. There are two major ways of detrending the series.

1) Trend stationary process
2) Difference stationary process

Trend stationary process:

$Y_t = f(t) + u_t$ $f(t) = \alpha + \beta t$ (linear trend)

$Y_t = \alpha + \beta t + ut$.

So, there is trend in the equation. We remove this trend. Apply OLS to the above equation

$\hat{Y} = \hat{\alpha} + \hat{\beta}t$. $\hat{Y}$ is estimated trend path.

Compute $\widehat{u_t} = Y_t - \widehat{Y_t}$.In this equation there is no trend.

$\widehat{u_t}$ is detrended series. It satisfies a) $\widehat{u_t}$=0 and $\sum t\,\hat{u}$

Nelson and Ploser called this model Trend Stationarity Process.

$Y_t = \alpha + \beta t + ut$

$E(Y_t) = \alpha + \beta t$.

$Var(Y_t) = \sigma_u^2$

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In case of TSP, mean depends on trend but variance does not depend on trend.

Difference stationary process

Here differencing is needed to obtain stationary.

$Y_t=\alpha+\beta t + u_t$.

$\Delta Y_t = \beta t + u_t - u_{t-1}$ so, $Y_t - Y_{t-1} = \beta + \varepsilon_t$.

Such a process is called Random Walk with drift. If the random walk model predicts that the value at time "t" will equal the last period's value plus a constant, or drift (β), and a white noise term (εt), then the process is random walk with a drift. It also does not revert to a long-run mean and has variance dependent on time.

$$\Delta^2 Y_t = u_t - 2u_{t-1} + u_{t-2}.$$

Such a process is called Random Walk without drift. Random walk predicts that the value at time "t" will be equal to the last period value plus a stochastic (non-systematic) component that is a white noise, which means εt is independent and identically distributed with mean "0" and variance "σ^2". Random walk can also be named a process integrated of some order, a process with a unit root or a process with a stochastic trend. It is a non mean reverting process that can move away from the mean either in a positive or negative direction. Another characteristic of a random walk is that the variance evolves over time and goes to infinity as time goes to infinity; therefore, a random walk cannot be predicted.

$Y_t - Y_{t-1} = \beta + \varepsilon t$

$E(Y_t - Y_{t-1}) = \beta$

$Var(Y_t) = t\sigma^2$. In case of DSP, mean does not depend on trend but variance depends on trend.

Test for TSP and DSP

$Y_t = \alpha + \rho Y_{t-1} + \beta t + \varepsilon t$

If ρ=1and β=0, the equation have no trend which implies DSP. If ρ<1 it implies TSP.

COINTEGRATION:

An important issue in econometrics is the need to integrate short run dynamics with long run equilibrium. The theory of co integration explains how to study the interrelationship between the

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long term trends in the variables, trends that are differenced away in the Box-Jenkins methods. This procedure, however, throws away potential valuable information about long run relationships about which economic theories have a lot to say.

A time series y_t is said to be integrated of order 1 or I(1) if Δ y_t is a stationary time series. A stationary time series is said to be I(0). A random walk is a special case of an I(1) series, because if y_t is a random walk, Δy_t is a random series or white noise. If y_t I(1), and ~I(0), then their sum $Z_t = y_t + u_t \sim$ I(1). ~

Suppose, $y_t - \beta x_t$ is I(0). This is denoted by saying y_t and x_t are CI (1,1). This means is that the regression equation $y_t = \beta x_t + u_t$.

This makes sense because y_t and x_t do not drift too far apart from each other over time. Thus there is a long run equilibrium relationship between them. If y_t and x_t are not cointegrated, that is $y_t - \beta x_t = u_t$. It is also I(1), they can drift apart from each other mare and mare as time goes on. Thus, there is no long run equilibrium relationship between them.

Definition of Cointegration: Suppose that ~ I(1), ~ I(1). Then y_t and x_t are said to be co integrated if there exists a β such that $y_t - \beta x_t$ is I(0). Cointegration relation is a long run relationship.

TEST FOR COINTEGRETION:

1) Apply unit root on y_t to see whether y_t is I(1).
2) Apply unit root on x_t to see whether x_t is I(1).
3) Apply OLS to obtain $\hat{u}_t$.
4) Apply unit root on $\hat{u}_t$ to see whether it is I(0).

Two step method of CI, which is

a) If y and x are CI then we get long run relationship.
b) If y and x is distributed then we get fluctuation computed by error correction method.

Error correction is done when a stable longrun trend exists and some kind of fluctuation is generated around it. And if stable longrun trend does not exists there error correction is not needed.

Bewly and **Wicknes** and **Brunch** showed that shortrun and longrun relationship can be estimated simultaneously. Now equation can be endogenous which is

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$Y_t = \beta x_t + \Delta y_t - \Delta x_t - v_t / \lambda$

This equation can be used for simultaneous estimators, but OLS is inappropriate. Use IV method. Use error correction method. Cotntegretion also support error correction method.

TESTING GOODNESS OF FIT FOR TIME SERIES MODEL

1) Akaiki Information Criteria (AIC)
2) Schwarz Bayesian Criteria (SBC)

The equations are-

$$\text{AIC (P)} = n \log \widehat{\sigma_p}^2 + 2p$$

$$\text{BIC (P)} = n \log \widehat{\sigma_p}^2 + p \log n$$

Where, n= sample size, p = total no of parameter, $\widehat{\sigma_p}^2$=RSS/n-p, RSS= Residual Sum Of Square Error. The model is chosen in the manner which is best fitted for which AIC or BIC minimum.

4. DATA

We have taken data on four variables - food grains production in India (F1), major commercial crop production in India (C1), Total Agricultural Production (C1+F1=T1) & institutional credit to the agricultural sector(L1) for the years 1970-2008. Commercial crops include oil seeds, cotton, raw jute & mesta, sugarcane, tobacco. The data on crop production is given in million tons while the data on agricultural credit is given in Rs. Crores. I look into the concepts of stationarity and co integration properties of our chosen datasets. The datasets are taken from the official website of the Reserve Bank of India. The data have been collected from the Reserve Bank of India database- time series publications, Handbook of Statistics on the Indian economy. The variables referred in the following empirical results denote the following:

L1: Total loans given to the agricultural sector by the institutional credit sources. It includes both loans issued and loans outstanding for years 1970-2008

F1: Total foodgrain production for years 1970-2008

C1: Total commercial crop production for years 1970-2008

T1: Total agricultural production for years 1970-2008 which includes both commercial and foodgrain production.

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4. ECONOMETRIC ANALYSIS

CORRELOGRAM:

Date: 10/29/13 Time: 11:36
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.905	0.905	34.459	0.000
		2	0.799	-0.111	62.031	0.000
		3	0.686	-0.094	82.915	0.000
		4	0.576	-0.047	98.052	0.000
		5	0.459	-0.106	107.97	0.000
		6	0.362	0.029	114.30	0.000
		7	0.261	-0.098	117.70	0.000
		8	0.178	0.020	119.34	0.000
		9	0.115	0.034	120.05	0.000
		10	0.065	-0.018	120.28	0.000
		11	0.024	0.001	120.31	0.000
		12	-0.012	-0.045	120.32	0.000
		13	-0.044	-0.030	120.44	0.000
		14	-0.075	-0.035	120.80	0.000
		15	-0.096	0.001	121.42	0.000
		16	-0.117	-0.029	122.38	0.000

Fig 1: The above figure shows the correlogram of the dependent variable of our model i.e total loans (L1) to the agricultural sector from the institutional sources. The correlogram is done to get a basic idea of which time series process the variable is following. Here we find that total loans follow an AR(1) process

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Date: 10/29/13 Time: 11:38
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.869	0.869	31.794	0.000
		2	0.813	0.234	60.346	0.000
		3	0.720	-0.105	83.389	0.000
		4	0.651	-0.007	102.77	0.000
		5	0.602	0.089	119.83	0.000
		6	0.522	-0.127	133.03	0.000
		7	0.498	0.126	145.42	0.000
		8	0.423	-0.114	154.65	0.000
		9	0.363	-0.097	161.69	0.000
		10	0.272	-0.149	165.77	0.000
		11	0.202	-0.004	168.09	0.000
		12	0.126	-0.093	169.04	0.000
		13	0.062	0.004	169.27	0.000
		14	0.007	-0.041	169.28	0.000
		15	-0.042	0.007	169.39	0.000
		16	-0.107	-0.157	170.20	0.000

Fig 2: The above figure shows the correlogram of the 1st independent variable i.e foodgrains production (F1). Here we find that total foodgrains production follow an AR(1) process.

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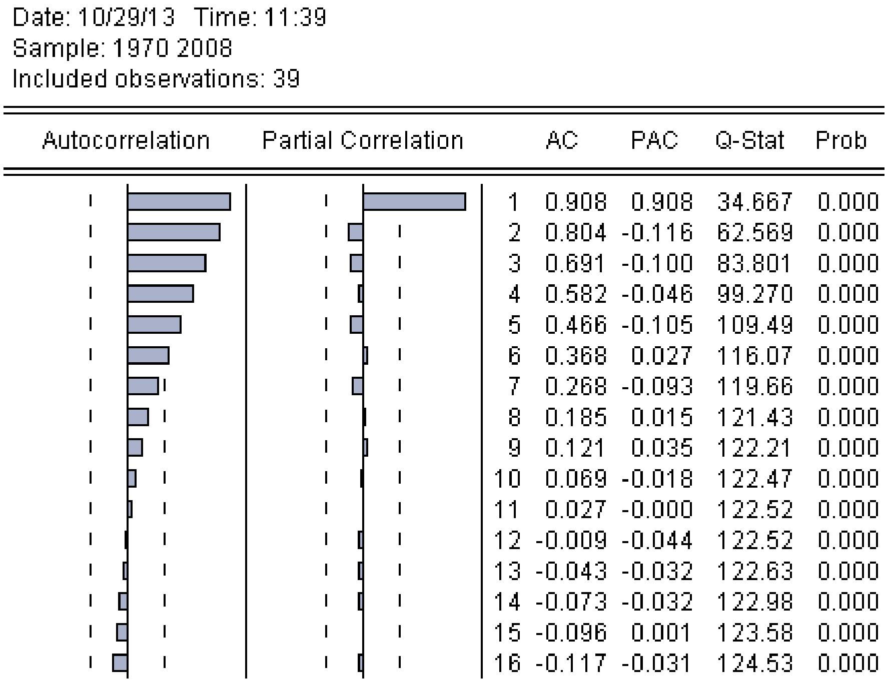

Date: 10/29/13 Time: 11:39
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.908	0.908	34.667	0.000
		2	0.804	-0.116	62.569	0.000
		3	0.691	-0.100	83.801	0.000
		4	0.582	-0.046	99.270	0.000
		5	0.466	-0.105	109.49	0.000
		6	0.368	0.027	116.07	0.000
		7	0.268	-0.093	119.66	0.000
		8	0.185	0.015	121.43	0.000
		9	0.121	0.035	122.21	0.000
		10	0.069	-0.018	122.47	0.000
		11	0.027	-0.000	122.52	0.000
		12	-0.009	-0.044	122.52	0.000
		13	-0.043	-0.032	122.63	0.000
		14	-0.073	-0.032	122.98	0.000
		15	-0.096	0.001	123.58	0.000
		16	-0.117	-0.031	124.53	0.000

Fig 3: The above figure shows the correlogram of the 2nd independent variable i.e commercial crop production (C1). It follows AR(1).

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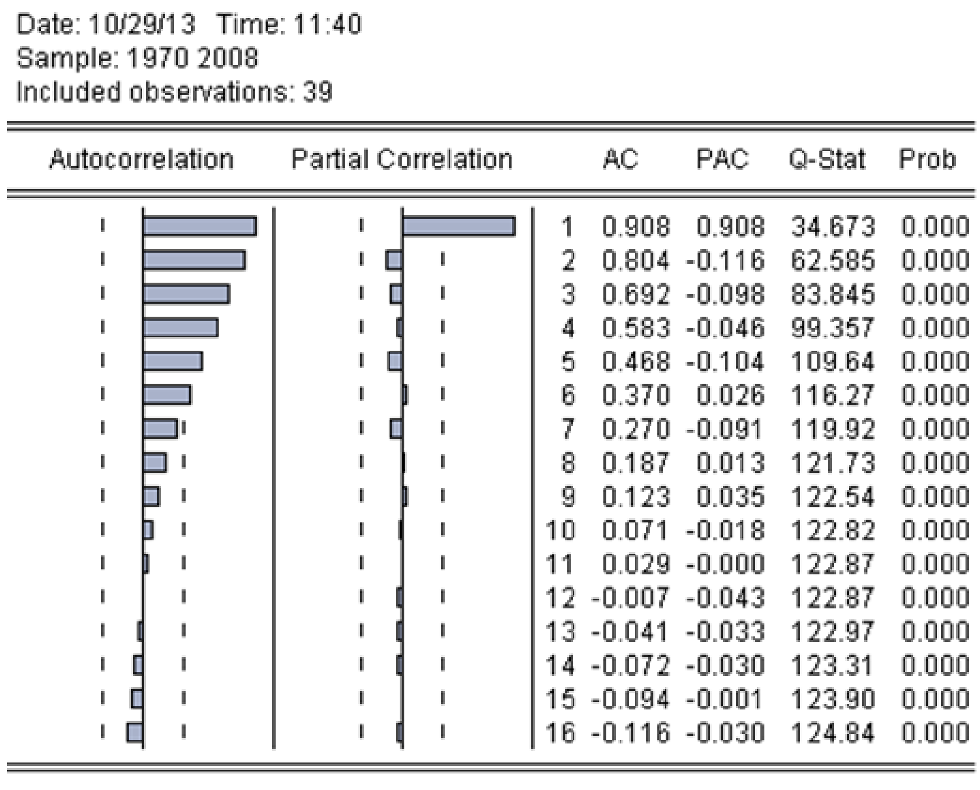

Date: 10/29/13 Time: 11:40
Sample: 1970 2008
Included observations: 39

	AC	PAC	Q-Stat	Prob
1	0.908	0.908	34.673	0.000
2	0.804	-0.116	62.585	0.000
3	0.692	-0.098	83.845	0.000
4	0.583	-0.046	99.357	0.000
5	0.468	-0.104	109.64	0.000
6	0.370	0.026	116.27	0.000
7	0.270	-0.091	119.92	0.000
8	0.187	0.013	121.73	0.000
9	0.123	0.035	122.54	0.000
10	0.071	-0.018	122.82	0.000
11	0.029	-0.000	122.87	0.000
12	-0.007	-0.043	122.87	0.000
13	-0.041	-0.033	122.97	0.000
14	-0.072	-0.030	123.31	0.000
15	-0.094	-0.001	123.90	0.000
16	-0.116	-0.030	124.84	0.000

Fig 4: The above figure shows the correlogram of the 3rd independent variable i.e total agricultural production(T1) which includes both the foodgrains as well as commercial crop production

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L1 correlogram (estimation)

Dependent Variable: SER05
Method: Least Squares
Date: 10/29/13 Time: 11:51
Sample (adjusted): 1971 2008
Included observations: 38 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.093800	0.014066	77.76252	0.0000

R-squared	0.990353	Mean dependent var	1761.256
Adjusted R-squared	0.990353	S.D. dependent var	2331.033
S.E. of regression	228.9543	Akaike info criterion	13.73089
Sum squared resid	1939543.	Schwarz criterion	13.77398
Log likelihood	-259.8868	Hannan-Quinn criter.	13.74622
Durbin-Watson stat	1.442789		

Inverted AR Roots	1.09
	Estimated AR process is nonstationary

Fig 5: By estimating the variable 'total loans'(T1) we find that the estimated AR process in non- stationary. So, we need to difference it till the AR process is stationary.

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ESTIMATION:

Dependent Variable: DSER05
Method: Least Squares
Date: 10/29/13 Time: 16:13
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1972

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.330427	0.222829	1.482870	0.1476
AR(2)	0.603575	0.188617	3.199996	0.0030
MA(1)	-0.145938	0.288609	-0.505659	0.6165

R-squared	0.553278	Mean dependent var	202.4517
Adjusted R-squared	0.526203	S.D. dependent var	282.5907
S.E. of regression	194.5153	Akaike info criterion	13.45855
Sum squared resid	1248595.	Schwarz criterion	13.59051
Log likelihood	-239.2540	Hannan-Quinn criter.	13.50461
Durbin-Watson stat	1.953810		

Inverted AR Roots	.96	-.63
Inverted MA Roots	.15	

Fig 7: Here we find that L1 follows ARMA(2,1). Correlogram for DF1(i.e first difference of D1)

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Date: 10/29/13 Time: 12:05
Sample: 1970 2008
ncluded observations: 38

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.633	-0.633	16.480	0.000
		2	0.300	-0.170	20.271	0.000
		3	-0.104	0.018	20.742	0.000
		4	-0.145	-0.282	21.687	0.000
		5	0.215	-0.064	23.813	0.000
		6	-0.201	-0.064	25.740	0.000
		7	0.116	-0.113	26.398	0.000
		8	0.026	0.046	26.431	0.001
		9	-0.074	0.035	26.719	0.002
		10	-0.020	-0.217	26.742	0.003
		11	0.125	0.090	27.618	0.004
		12	-0.221	-0.107	30.481	0.002
		13	0.224	-0.087	33.535	0.001
		14	-0.227	-0.151	36.809	0.001
		15	0.190	0.004	39.196	0.001
		16	-0.018	0.059	39.217	0.001

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Estimation of DF1 (1st difference of F1):

Dependent Variable: DSER06
Method: Least Squares
Date: 10/29/13 Time: 12:13
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments
Convergence achieved after 15 iterations
MA Backcast: 1972

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.351067	0.133018	2.639249	0.0126
AR(2)	0.632871	0.135023	4.687129	0.0000
MA(1)	-0.968855	0.021640	-44.77095	0.0000

R-squared	0.408499	Mean dependent var	3.817778
Adjusted R-squared	0.372650	S.D. dependent var	14.85163
S.E. of regression	11.76330	Akaike info criterion	7.847501
Sum squared resid	4566.382	Schwarz criterion	7.979461
Log likelihood	-138.2550	Hannan-Quinn criter.	7.893559
Durbin-Watson stat	2.261596		

Inverted AR Roots	.99	-.64
Inverted MA Roots	.97	

Fig 8: DF1 follows ARMA (2,1).

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Correlogram of DF2 (1st difference of F2)

Date: 10/29/13 Time: 12:16
Sample: 1970 2008
Included observations: 38

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.575	0.575	13.595	0.000
		2	0.720	0.581	35.473	0.000
		3	0.544	0.081	48.313	0.000
		4	0.427	-0.293	56.478	0.000
		5	0.385	-0.084	63.303	0.000
		6	0.251	-0.000	66.307	0.000
		7	0.163	-0.112	67.611	0.000
		8	0.037	-0.214	67.681	0.000
		9	0.077	0.238	67.991	0.000
		10	-0.024	0.194	68.022	0.000
		11	-0.012	-0.110	68.030	0.000
		12	-0.060	-0.198	68.237	0.000
		13	-0.097	-0.015	68.809	0.000
		14	-0.103	0.023	69.476	0.000
		15	-0.120	-0.083	70.427	0.000
		16	-0.132	-0.056	71.625	0.000

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Estimation of DC1(1st difference of C1)

Dependent Variable: DSER07
Method: Least Squares
Date: 10/29/13 Time: 12:19
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments
Convergence achieved after 14 iterations
MA Backcast: 1972

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.328761	0.231903	1.417662	0.1657
AR(2)	0.596478	0.194988	3.059048	0.0044
MA(1)	-0.108949	0.301679	-0.361142	0.7203

R-squared	0.556354	Mean dependent var	520.1125
Adjusted R-squared	0.529467	S.D. dependent var	711.5212
S.E. of regression	488.0710	Akaike info criterion	15.29845
Sum squared resid	7861037.	Schwarz criterion	15.43041
Log likelihood	-272.3722	Hannan-Quinn criter.	15.34451
Durbin-Watson stat	1.930046		

Inverted AR Roots	.95	-.63
Inverted MA Roots	.11	

Fig 10: DC1 follows ARMA(2,1)

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Estimation of DT1(1st difference of T1)

Dependent Variable: DSER08
Method: Least Squares
Date: 10/29/13 Time: 12:26
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1972

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.340783	0.236766	1.439320	0.1595
AR(2)	0.586723	0.199838	2.935992	0.0060
MA(1)	-0.113225	0.305431	-0.370705	0.7132

R-squared	0.559269	Mean dependent var	523.9303
Adjusted R-squared	0.532558	S.D. dependent var	707.4377
S.E. of regression	483.6733	Akaike info criterion	15.28035
Sum squared resid	7720015.	Schwarz criterion	15.41231
Log likelihood	-272.0463	Hannan-Quinn criter.	15.32641
Durbin-Watson stat	1.929461		

Inverted AR Roots	.96	-.61
Inverted MA Roots	.11	

Fig 11: DT1 follows ARMA (2,1)

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Correlogram estimation of C1

Dependent Variable: SER07
Method: Least Squares
Date: 10/29/13 Time: 12:30
Sample (adjusted): 1971 2008
Included observations: 38 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.090011	0.013517	80.64277	0.0000

R-squared	0.990731	Mean dependent var	4757.886
Adjusted R-squared	0.990731	S.D. dependent var	6034.660
S.E. of regression	580.9898	Akaike info criterion	15.59331
Sum squared resid	12489317	Schwarz criterion	15.63640
Log likelihood	-295.2728	Hannan-Quinn criter.	15.60864
Durbin-Watson stat	1.341383		

Inverted AR Roots	1.09
	Estimated AR process is nonstationary

Fig 12: the above figure shows that the estimated AR process of C1 is non-stationary. So, we need to difference it to obtain stationarity.

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Correlogram Estimation of T1:

Dependent Variable: SER08
Method: Least Squares
Date: 10/29/13 Time: 12:31
Sample (adjusted): 1971 2008
Included observations: 38 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.089265	0.013103	83.12902	0.0000

R-squared	0.991073	Mean dependent var	4922.252
Adjusted R-squared	0.991073	S.D. dependent var	6065.994
S.E. of regression	573.1386	Akaike info criterion	15.56610
Sum squared resid	12154052	Schwarz criterion	15.60919
Log likelihood	-294.7558	Hannan-Quinn criter.	15.58143
Durbin-Watson stat	1.325590		

Inverted AR Roots	1.09
	Estimated AR process is nonstationary

Fig 13: the above figure shows that the estimated AR process of T1 is non-stationary. So, we need to difference it in order to obtain stationarity.

The stationarity of L1 is obtained at the fourth differencing i.e at DDDDL1.

<u>Correlogram Analysis for Stationarity</u>

The stationarity of the variables has been examined through the study of their Auto-correlation functions (ACFs) & Partial Auto-correlation Functions (PACFs). Figures 1-4 represent the ACF & PACFs of the variables concerned. It is observed from these functions that the series for L1,C1, F1 & T1 are non-stationary.

<u>Test of Unit Roots</u>

In case of time series analysis, unit root tests are important since these tests detect the stationarity and non-stationarity of the time series data used for the study. Regression run on non-stationary time series produces spurious relations. To avoid this, it becomes necessary to perform a unit root test on the variables. The Augmented Dickey-Fuller (ADF) test is widely used for performing unit root test.

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Now, I perform the unit root test to detect whether the datasets are stationary or non-stationary.

Augmented Dickey-Fuller Tests for unit roots

UNIT ROOT TEST:

Unit Root Test of DDDDL1:

Null Hypothesis: DDDDSER05 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on AIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.48618	0.0000
Test critical values:	1% level	-4.309824	
	5% level	-3.574244	
	10% level	-3.221728	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DDDDSER05)
Method: Least Squares
Date: 10/29/13 Time: 12:42
Sample (adjusted): 1980 2008
Included observations: 29 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DDDDSER05(-1)	-16.73558	1.595965	-10.48618	0.0000
D(DDDDSER05(-1))	13.44409	1.528904	8.793287	0.0000
D(DDDDSER05(-2))	10.49826	1.326938	7.911641	0.0000
D(DDDDSER05(-3))	7.496121	1.000930	7.489159	0.0000
D(DDDDSER05(-4))	4.573456	0.626249	7.302938	0.0000
D(DDDDSER05(-5))	1.839464	0.245426	7.494972	0.0000
C	93.67744	91.71968	1.021345	0.3187
@TREND("1970")	-5.042592	3.666167	-1.375440	0.1835

R-squared	0.995355	Mean dependent var	21.78172
Adjusted R-squared	0.993806	S.D. dependent var	2023.585
S.E. of regression	159.2572	Akaike info criterion	13.20787
Sum squared resid	532620.2	Schwarz criterion	13.58505
Log likelihood	-183.5141	Hannan-Quinn criter.	13.32600
F-statistic	642.8096	Durbin-Watson stat	1.661126
Prob(F-statistic)	0.000000		

H0: DDDDL1 has a unit root. H1: DDDDL1 does not have a unit root.

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The above figure shows the null hypothesis is rejected so it implies that DDDDL1 does not have a unit root.

Unit Root test of DF1:

Null Hypothesis: DSER06 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.43035	0.0000
Test critical values:	1% level	-4.226815	
	5% level	-3.536601	
	10% level	-3.200320	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DSER06)
Method: Least Squares
Date: 10/29/13 Time: 12:45
Sample (adjusted): 1972 2008
Included observations: 37 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSER06(-1)	-1.637421	0.131728	-12.43035	0.0000
C	3.637699	4.088125	0.889821	0.3798
@TREND("1970")	0.098243	0.180313	0.544849	0.5894

R-squared	0.819665	Mean dependent var	0.187568
Adjusted R-squared	0.809057	S.D. dependent var	26.75710
S.E. of regression	11.69207	Akaike info criterion	7.833303
Sum squared resid	4647.953	Schwarz criterion	7.963918
Log likelihood	-141.9161	Hannan-Quinn criter.	7.879351
F-statistic	77.26877	Durbin-Watson stat	2.211121
Prob(F-statistic)	0.000000		

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Null Hypothesis: DDDDSER07 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on AIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.13631	0.0000
Test critical values:	1% level	-4.309824	
	5% level	-3.574244	
	10% level	-3.221728	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DDDDSER07)
Method: Least Squares
Date: 10/29/13 Time: 15:34
Sample (adjusted): 1980 2008
Included observations: 29 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DDDDSER07(-1)	-16.71926	1.649442	-10.13631	0.0000
D(DDDDSER07(-1))	13.40123	1.575877	8.503981	0.0000
D(DDDDSER07(-2))	10.39949	1.359722	7.648250	0.0000
D(DDDDSER07(-3))	7.334895	1.017232	7.210639	0.0000
D(DDDDSER07(-4))	4.407022	0.632058	6.972502	0.0000
D(DDDDSER07(-5))	1.735904	0.247985	7.000040	0.0000
C	233.1616	239.2379	0.974601	0.3409
@TREND("1970")	-12.48000	9.550032	-1.306802	0.2054

R-squared	0.994665	Mean dependent var	63.76379
Adjusted R-squared	0.992887	S.D. dependent var	4932.431
S.E. of regression	416.0041	Akaike info criterion	15.12822
Sum squared resid	3634247.	Schwarz criterion	15.50540
Log likelihood	-211.3592	Hannan-Quinn criter.	15.24635
F-statistic	559.3245	Durbin-Watson stat	1.680556
Prob(F-statistic)	0.000000		

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Unit root test of DDDDT1

Null Hypothesis: DDDDSER08 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on AIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.637533	0.0000
Test critical values:	1% level	-4.309824	
	5% level	-3.574244	
	10% level	-3.221728	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DDDDSER08)
Method: Least Squares
Date: 10/29/13 Time: 15:37
Sample (adjusted): 1980 2008
Included observations: 29 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DDDDSER08(-1)	-16.61177	1.723654	-9.637533	0.0000
D(DDDDSER08(-1))	13.28261	1.645644	8.071375	0.0000
D(DDDDSER08(-2))	10.27283	1.419075	7.239101	0.0000
D(DDDDSER08(-3))	7.222786	1.060327	6.811849	0.0000
D(DDDDSER08(-4))	4.319102	0.657104	6.572939	0.0000
D(DDDDSER08(-5))	1.688976	0.258327	6.538129	0.0000
C	232.0004	247.0932	0.938919	0.3584
@TREND("1970")	-12.30128	9.861509	-1.247403	0.2260

R-squared	0.994016	Mean dependent var	62.45759
Adjusted R-squared	0.992022	S.D. dependent var	4809.977
S.E. of regression	429.6369	Akaike info criterion	15.19271
Sum squared resid	3876345.	Schwarz criterion	15.56989
Log likelihood	-212.2943	Hannan-Quinn criter.	15.31084
F-statistic	498.3521	Durbin-Watson stat	1.793559
Prob(F-statistic)	0.000000		

Fig 17: DDDDT1 has no unit root because the null hypothesis which states that there is unit root is rejected.

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Correlogram of DDDDT1

Date: 10/29/13 Time: 15:39
Sample: 1970 2008
Included observations: 35

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.853	-0.853	27.702	0.000
		2	0.525	-0.742	38.518	0.000
		3	-0.213	-0.538	40.358	0.000
		4	0.027	-0.289	40.388	0.000
		5	0.035	-0.157	40.440	0.000
		6	-0.053	-0.450	40.568	0.000
		7	0.108	-0.231	41.107	0.000
		8	-0.178	0.126	42.627	0.000
		9	0.199	0.176	44.606	0.000
		10	-0.161	-0.021	45.943	0.000
		11	0.091	-0.080	46.393	0.000
		12	-0.028	0.007	46.438	0.000
		13	-0.006	-0.077	46.439	0.000
		14	0.016	-0.230	46.455	0.000
		15	-0.019	-0.109	46.479	0.000
		16	0.015	-0.001	46.494	0.000

Correlogram of DDDDC1:

Date: 10/29/13 Time: 15:41
Sample: 1970 2008
Included observations: 35

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.857	-0.857	27.984	0.000
		2	0.538	-0.740	39.356	0.000
		3	-0.232	-0.532	41.539	0.000
		4	0.043	-0.292	41.616	0.000
		5	0.027	-0.155	41.649	0.000
		6	-0.056	-0.448	41.790	0.000
		7	0.117	-0.220	42.418	0.000
		8	-0.188	0.146	44.105	0.000
		9	0.207	0.181	46.233	0.000
		10	-0.166	-0.034	47.660	0.000
		11	0.097	-0.089	48.168	0.000
		12	-0.035	0.006	48.237	0.000
		13	0.002	-0.069	48.237	0.000
		14	0.008	-0.241	48.241	0.000
		15	-0.010	-0.109	48.248	0.000
		16	0.006	0.023	48.250	0.000

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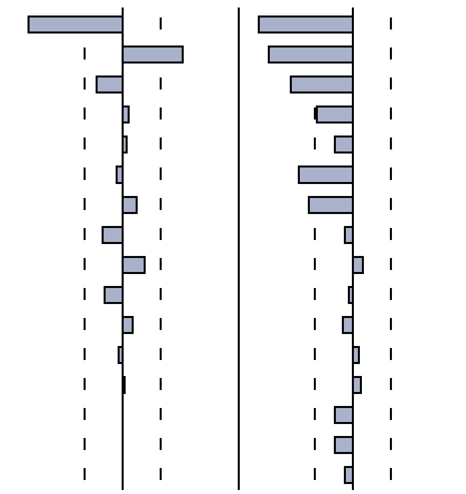
Correlogram of DDDDL1

Date: 10/29/13 Time: 15:43
Sample: 1970 2008
Included observations: 35

Autocorrelation | Partial Correlation



	AC	PAC	Q-Stat	Prob
1	-0.858	-0.858	28.059	0.000
2	0.540	-0.747	39.503	0.000
3	-0.234	-0.559	41.712	0.000
4	0.045	-0.330	41.798	0.000
5	0.026	-0.157	41.827	0.000
6	-0.059	-0.479	41.984	0.000
7	0.121	-0.396	42.664	0.000
8	-0.187	-0.076	44.336	0.000
9	0.200	0.092	46.323	0.000
10	-0.157	-0.046	47.595	0.000
11	0.091	-0.098	48.043	0.000
12	-0.037	0.043	48.119	0.000
13	0.010	0.067	48.125	0.000
14	-0.003	-0.163	48.126	0.000
15	0.001	-0.167	48.126	0.000
16	-0.005	-0.075	48.127	0.000

Estimation of DDDDL1:

Dependent Variable: DDDDSER05
Method: Least Squares
Date: 10/29/13 Time: 15:53
Sample (adjusted): 1975 2008
Included observations: 34 after adjustments
Convergence achieved after 19 iterations
MA Backcast: OFF (Roots of MA process too large)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.840178	0.100536	-8.356964	0.0000
MA(1)	-1.096673	0.082532	-13.28780	0.0000

R-squared	0.918746	Mean dependent var	0.333235
Adjusted R-squared	0.916207	S.D. dependent var	968.8208
S.E. of regression	280.4452	Akaike info criterion	14.16766
Sum squared resid	2516783.	Schwarz criterion	14.25744
Log likelihood	-238.8501	Hannan-Quinn criter.	14.19828
Durbin-Watson stat	2.848092		

Inverted AR Roots	-.84
Inverted MA Roots	1.10
	Estimated MA process is noninvertible

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The above table shows that DDDDL1 follows ARMA (1,1)

Estimation of DDDDC1:

Dependent Variable: DDDDSER07
Method: Least Squares
Date: 10/29/13 Time: 15:57
Sample (adjusted): 1975 2008
Included observations: 34 after adjustments
Convergence achieved after 7 iterations
MA Backcast: OFF (Roots of MA process too large)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.836055	0.099054	-8.440403	0.0000
MA(1)	-1.135762	0.028966	-39.20980	0.0000

R-squared	0.924563	Mean dependent var	6.410882
Adjusted R-squared	0.922205	S.D. dependent var	2364.453
S.E. of regression	659.4856	Akaike info criterion	15.87782
Sum squared resid	13917480	Schwarz criterion	15.96761
Log likelihood	-267.9229	Hannan-Quinn criter.	15.90844
Durbin-Watson stat	2.922874		

Inverted AR Roots	-.84
Inverted MA Roots	1.14
	Estimated MA process is noninvertible

The above table shows that DDDDC1 follows ARMA(1,1)

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Estimation of DDDDT1:

Dependent Variable: DDDDSER08
Method: Least Squares
Date: 10/29/13 Time: 15:59
Sample (adjusted): 1975 2008
Included observations: 34 after adjustments
Convergence achieved after 11 iterations
MA Backcast: OFF (Roots of MA process too large)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.837229	0.100357	-8.342542	0.0000
MA(1)	-1.095394	0.029984	-36.53259	0.0000

R-squared	0.918848	Mean dependent var	6.812059
Adjusted R-squared	0.916312	S.D. dependent var	2309.381
S.E. of regression	668.0789	Akaike info criterion	15.90371
Sum squared resid	14282542	Schwarz criterion	15.99350
Log likelihood	-268.3631	Hannan-Quinn criter.	15.93433
Durbin-Watson stat	2.900017		

Inverted AR Roots	-.84
Inverted MA Roots	1.10
	Estimated MA process is noninvertible

The above table shows that DDDDT1 follows ARMA(1,1)

COINTEGRATION:

Cointegration between L1 and F1:

Dependent Variable: DDDSER05
Method: Least Squares
Date: 10/29/13 Time: 16:36
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	100.7367	379.1295	0.265705	0.7921
SER06	-0.638824	2.203399	-0.289927	0.7736

R-squared	0.002466	Mean dependent var	-6.509444
Adjusted R-squared	-0.026873	S.D. dependent var	492.0931
S.E. of regression	498.6613	Akaike info criterion	15.31568
Sum squared resid	8454544.	Schwarz criterion	15.40366
Log likelihood	-273.6823	Hannan-Quinn criter.	15.34639
F-statistic	0.084057	Durbin-Watson stat	3.649034
Prob(F-statistic)	0.773633		

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Unit root of residual

Null Hypothesis: RDDDSER05 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 7 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.332852	0.8582
Test critical values:	1% level	-4.323979	
	5% level	-3.580623	
	10% level	-3.225334	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RDDDSER05)
Method: Least Squares
Date: 10/29/13 Time: 16:38
Sample (adjusted): 1981 2008
Included observations: 28 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RDDDSER05(-1)	-3.219517	2.415510	-1.332852	0.1992
D(RDDDSER05(-1))	1.155228	2.417041	0.477951	0.6384
D(RDDDSER05(-2))	0.641500	2.324827	0.275934	0.7857
D(RDDDSER05(-3))	0.414536	2.101090	0.197296	0.8458
D(RDDDSER05(-4))	0.083922	1.786706	0.046970	0.9631
D(RDDDSER05(-5))	-0.148672	1.519047	-0.097872	0.9231
D(RDDDSER05(-6))	0.127179	1.125624	0.112986	0.9113
D(RDDDSER05(-7))	1.023204	0.582925	1.755292	0.0962
C	-54.12648	164.6378	-0.328761	0.7461
@TREND("1970")	3.058389	7.018599	0.435755	0.6682

R-squared	0.984073	Mean dependent var	3.586066
Adjusted R-squared	0.976109	S.D. dependent var	1068.905
S.E. of regression	165.2163	Akaike info criterion	13.32484
Sum squared resid	491335.5	Schwarz criterion	13.80063
Log likelihood	-176.5478	Hannan-Quinn criter.	13.47029
F-statistic	123.5723	Durbin-Watson stat	2.017663
Prob(F-statistic)	0.000000		

The above table shows that the cointegration between L1 and F1. There is no cointegration in the long run between L1 and F1.

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Cointegration between L1 and C1:

Dependent Variable: DDDSER05
Method: Least Squares
Date: 10/29/13 Time: 16:39
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.340589	4.664444	-0.073018	0.9422
DDDSER07	0.409030	0.003938	103.8681	0.0000

R-squared	0.996858	Mean dependent var	-6.509444
Adjusted R-squared	0.996766	S.D. dependent var	492.0931
S.E. of regression	27.98440	Akaike info criterion	9.555124
Sum squared resid	26626.30	Schwarz criterion	9.643097
Log likelihood	-169.9922	Hannan-Quinn criter.	9.585829
F-statistic	10788.58	Durbin-Watson stat	3.114259
Prob(F-statistic)	0.000000		

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Unit root test

Null Hypothesis: RDDDSER05 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.313952	0.0000
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RDDDSER05)
Method: Least Squares
Date: 10/29/13 Time: 16:45
Sample (adjusted): 1977 2008
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RDDDSER05(-1)	-5.637158	0.678036	-8.313952	0.0000
D(RDDDSER05(-1))	3.254854	0.585353	5.560496	0.0000
D(RDDDSER05(-2))	1.745126	0.380592	4.585295	0.0001
D(RDDDSER05(-3))	0.738185	0.161197	4.579393	0.0001
C	-6.181570	5.646106	-1.094838	0.2836
@TREND("1970")	0.473327	0.236746	1.999303	0.0561

R-squared	0.952536	Mean dependent var	-2.839256
Adjusted R-squared	0.943409	S.D. dependent var	50.67981
S.E. of regression	12.05619	Akaike info criterion	7.984393
Sum squared resid	3779.142	Schwarz criterion	8.259219
Log likelihood	-121.7503	Hannan-Quinn criter.	8.075490
F-statistic	104.3574	Durbin-Watson stat	2.079802
Prob(F-statistic)	0.000000		

Fig 25: This figure shows the cointegration between L1 and C1. There is cointegration in the long run between L1 and C1.

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Cointegration between L1 and T1:

Dependent Variable: DDDSER05
Method: Least Squares
Date: 10/29/13 Time: 16:46
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.159127	7.210260	-0.022070	0.9825
DDDSER08	0.417281	0.006224	67.04716	0.0000

R-squared	0.992493	Mean dependent var	-6.509444
Adjusted R-squared	0.992273	S.D. dependent var	492.0931
S.E. of regression	43.25783	Akaike info criterion	10.42619
Sum squared resid	63622.14	Schwarz criterion	10.51416
Log likelihood	-185.6714	Hannan-Quinn criter.	10.45689
F-statistic	4495.322	Durbin-Watson stat	3.356936
Prob(F-statistic)	0.000000		

Unit root test:

Null Hypothesis: RDDDSER05 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.126878	0.0000
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RDDDSER05)
Method: Least Squares
Date: 10/29/13 Time: 16:48
Sample (adjusted): 1977 2008
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RDDDSER05(-1)	-5.502811	0.772121	-7.126878	0.0000
D(RDDDSER05(-1))	3.011565	0.662186	4.547914	0.0001
D(RDDDSER05(-2))	1.499508	0.421820	3.554849	0.0015
D(RDDDSER05(-3))	0.557726	0.164849	3.383257	0.0023
C	-8.917268	8.397928	-1.061841	0.2981
@TREND("1970")	0.572572	0.348993	1.640639	0.1129

R-squared	0.958335	Mean dependent var	-3.463216
Adjusted R-squared	0.950322	S.D. dependent var	80.59732
S.E. of regression	17.96392	Akaike info criterion	8.781968
Sum squared resid	8390.261	Schwarz criterion	9.056794
Log likelihood	-134.5115	Hannan-Quinn criter.	8.873065
F-statistic	119.6047	Durbin-Watson stat	2.091624
Prob(F-statistic)	0.000000		

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The above table shows the cointegration between L1 and T1. There is cointegration in the long run between L1 and T1.

IDENTIFICATION OF THE STOCHASTIC PROCESS

The Box-Jenkins methodology is used to diagnose the stochastic process generating the time series. To find the appropriate stochastic process and the optimal lag lengths we take the help of Correlograms given in figures 1 to 4.

If the autocorrelations taper off slowly or do not die out, non-stationarity is indicated and differencing is suggested until stationarity is obtained. Then an ARMA model is identified for the differenced series.

For an MA(p) process the autocorrelations $a_k=0$ for $k>p$. and the partial autocorrelations taper off. To determine a cut off point of the ACF the sample autocorrelations are used.

For an AR(q) the partial autocorrelations $b_{kk}=0$ for $k>q$ and the autocorrelations taper off. If the spikes of the PACF are significant through q then this determines the degree of AR process.

If neither the autocorrelations nor the partial autocorrelations have a cut off point an ARMA model may be adequate. The AR and the MA degree have to be inferred from the particular patterns of autocorrelations and partial autocorrelations. We find that neither the ACF nor the PACF have a cut off point for the series DL1,DF1, DC1 and DT1. Hence we conclude that the series follow ARMA process.DL1 follows ARMA(2,1),DF1 follows ARMA(2,1) while DC1 follows ARMA(2,1) and DT1 follows ARMA(2,1). These results are rough estimates. They are not supported by any regression analysis.

Co- integration

Co-integration between the time series are studied for estimating a stable long-run equilibrium relationship between the variables concerned. This concept is very useful in empirical analysis because it allows the research to describe the nature of an equilibrium or stationarity relationship between two time series each of which is individually non-stationary.

In our study, we have found that the time series L1,C1,T1 are non stationary at the level. is stationary at the fourth difference, which implies that it is integrated of order three, I(3) and F1 is stationary at the first differencing so it is integrated of order one i.e I(1).In our study, we have taken the series L1, the institutional credit to agricultural sector of india over the time period 1970-2008 as an independent variable, whereas the commercial crop production, C1, food grains production, F1 & the total agricultural production T1, over that time period are taken as the

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dependent variables respectively. We want to check, whether there is any longrun stable relationship between the independent variable L1 & each of the dependent variables, C1, F1, T1.

For the study of co-integration between the variables concerned, the following procedures have been adopted-

- The co-integrating equation has been estimated with the OLS method. The non-stationarity of the series under study can be removed by differencing the series, generally the series are integrated of order d, where d>0. Hence the regressand & the regressors of the co- integrating equation are I(d), d>0.
- The residuals of the estimated equation have been obtained. The residuals are the linear combination of the variables which are I(d), included in the equation.
- The residuals are subject to ADF test to examine if random walk exists or if the residuals are white noise, meaning if the residual are I(0).

If the residuals are I(0), then we conclude that the variables are cointegrated otherwise not.

6. CONCLUSION

From the above econometric analysis, we've found that there is no co integration of institutional credit with production of foodgrains but cointegration exists with production of commercial crops and total agricultural production. This result has some major economic perspective:

Firstly, credit, if considered as an input to agriculture, is the source of monetary capital to the farmers. More specifically, Indian farmers, most of them belonging to low or middle income groups, initially buy capital, raw materials etc with credit because of lack of personal funds. If more credit is issued to the farmers, they can use improved techniques to obtain better produces. So, it can be inferred that Indian agriculture can improve a lot if sufficient amount of credit is issued to agricultural sector and if the issued fund is used efficiently. So higher the credit higher is the agricultural production. *Secondly,* to be more specific, we've considered institutional credit, which means loans issued by commercial banks, regional rural banks and co-operative banks. The obtained non co integration may also result from the dominance of non-institutional credit sources like moneylenders in India. Most of the banks still avoid agricultural sector while issuing credit because of high default rate of farmers. So, the farmers have to depend on non institutional credit sources. Besides, complex credit policies have also refrained the farmers from taking a step towards institutional sources. *Thirdly,* dependence on monsoon and family farming system has created a sort of vicious cycle in Indian agriculture. Family farming process is coupled with disguised unemployment and low productivity. Besides, dependence on monsoon results in fluctuation in agricultural production, which means farmers' default rate increases in

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times of bad monsoon, so banks do not issue credit to them. In turn, lack of fund compels the farmers to stick to old production techniques, behavior of monsoon and non-institutional sources of credit charging high interest rates. So, productivity doesn't rise significantly.

REMARKS

Macro-Economic variables, which are used in this study viz. food grains production (F1), commercial crop production (C1), total agricultural production (P1) and institutional credit (L1) to the agricultural sector, are of time series by nature. These series are not deterministic variables. On the contrary these are considered to be generated by some underlying stochastic processes. Except the series L1 all others show non-stationary at the level. We have taken help of the Box-Jenkins approach to model the time series under study. It has been found that institutional credit (L1) follows an ARMA (2,1) process while foodgrains production (F1), commercial crop production(C1) and total agricultural production(P1) follow ARMA processes respectively. The lag lengths for the ARMA processes couldn't be computed though a rough idea could be obtained by studying the Correlogram. Through Correlogram analysis it has been found that food grains production(F1) follows an ARMA(2,1) process while , commercial crop production (C1) follows an ARMA (2,1) process and total agricultural production (T1) has been generated by the ARMA (2,1) stochastic process.

The time series for food grains production (F1), commercial crop production (C1), total agricultural production (T1) and institutional credit (L1) to the agricultural sector have been subject to tests for stationary. In this study the Augmented Dickey-Fuller method has been adopted for the test of the presence of unit roots for the time series concerned. Unit root tests are undertaken to examine whether the time series exhibit random walk process, i.e. non-stationary. Results such as L1,F1, C1 and P1 have been found to be non stationary Thus L1,F1, C1 and T1 are differenced to make them stationary. L1,C1 and P1 are integrated of order 3 while F1 is I (1).

Non-stationary of the series F1, C1, T1 and L1 at level have further been verified through the estimation the Autocorrelation functions (ACF) and Partial Autocorrelation Function (PACF). The ACF and PACF plots showing the estimated coefficients for different lags along with the upper and lower critical values for the confidence limit have been derived. The plot of ACF and PACF against the lag lengths is known as Correlogram. Through Correlogram analysis it has been verified that L1,F1, C1 and P1 become stationary at fourth difference. In our analysis no co-integration has been found between the time series. There exist no co integration between institutional credit and agricultural food grain production but there exists co integration between institutional credit and commercial crop production & also between institutional credit and total agricultural production.

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Institutional credit plays an important role in enhancing the agricultural productivity in developing countries like India. The study discusses about the need for institutional credit followed by a brief about the birth of Institutional credit in India. The paper also discusses the Bank Reforms of India and the impact on the farmers. The study talks about the aversion of the private banks from providing credits to agriculture and the consequences due to it.

It then speaks about the benefits of providing institutional credit for the agricultural sector, but discusses the issues faced by the financial institutions for providing healthy credit. During the study it was found that the Institutional credit has been increasing over the years and there is a direct relation of credit with food grains production. An IMF study over 50 countries ranging from 1980 to 2003 has found evidence of a direct relation between increase in institutional credit and agricultural productivity. The future lies in an alliance between financial institutions and Self-Help groups to provide accessible credit to farmers and provide a win-win situation for the commercial banks.

In India, 70% of the total workforce is employed in agricultural and related sectors. The contribution of agricultural sector towards GDP is 19.9%. Growths of industry and service sectors are also directly linked to agricultural growth. Therefore, in order to achieve a GDP growth of more than 8%, agricultural sector should exhibit a commensurate growth. However, growth of agriculture over the last 10 years has been less than 1.5% per annum. Such a low rate of growth can be attributed to different factors such as low/high monsoon, unavailability of farming equipments and fertilizers, irrigation problems, unavailability of funds etc. institutional credit is required to boost the agricultural sector.

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