Effect of Rainfall on Seasonals in Indian Manufacturing Production: Evidence from Sectoral Data

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Abstract

Recent research has shown that the seasonals in Indian manufacturing production are affected by rainfall. Since the effect of rainfall comes through agricultural production, this finding raises the question of whether the effect is through demand channel or supply channel. This paper attempts to provide a preliminary answer to this question by testing for this effect in the production in different sub-sectors within the manufacturing sector. We look at the three subsectors which have more than 10% weightage each in the index of manufacturing production: (i) food products, (ii) basic chemicals and chemical products (except products of petroleum and coal), and (iii) machinery and equipment (other than transport equipment). As almost all the estimated models show some type of misspecification, we also estimate models that allow for time-variation in this behaviour. We find evidence for effect of rainfall on overall dynamics of all three components studied, and also for significant time variation in this behaviour. Focusing on seasonal component, while estimations were not possible for the basic chemicals and chemical products, for the other two components we find evidence of significant effect of rainfall on seaosonality, indicating both the channels are significant.

JEL Classification codes: C22, E32.

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1 Introduction

Seasonal fluctuations account for a large fraction of variation in industrial production in most countries. Due to this, seasonal adjustment has been the first step in analysis of such series, for a long time. However, past two decades have seen surge in interest in modelling seasonal fluctuations, since it has been argued that seasonal fluctuations are not that regular and contain important information about the economy(e.g., Cechhetti, Kashyap and Wilcox, 1997).

Indian economy shows strong seasonal character, to a large extent due to the heavy dependence of the economy on agriculture. Dua and Kumawat (2005) found the seasonal fluctuations in industrial production to be related to the stochastic trend in this variable, and opined that the seasonal fluctuations may be caused by the variations in agricultural output, which is primarily dependent on rainfall. Kumawat (2009) found statistical evidence for this, through manufacturing sector. The next question then is, what is the channel through which the fluctuations in the agricultural production cause the seasonals in manufacturing production to vary. It could be demand channel: agricultural sector provides employment to more than half of India's labour force, therefore accounting for a large part of total demand. Further, agriculture also requires the industrial output as its capital goods. On the other hand, a large number of industries receive their raw materials from agriculture, and this provides the supply channel for the effect of agriculture on industry. In this paper, an attempt has been made to provide a preliminary answer to this question by testing for the effect of rainfall on major components of manufacturing output. One additional issue here is the possible time variation. The Indian economy has undergone substantial institutional changes during last three decades and one would expect this to affect the dynamics of manufacturing production as well, and possibly seasonal dynamics. We allow for this type of variation as well, to correct for misspecification, wherever indicated by tests.

We find that dynamics of all the three components studied here, namely, (i) food products (two-digit classification code 20 and 21), (ii) basic chemical and chemical products (except products of petroleum and coal, code 30), and (iii) machinery and equipment other than transport equipment (code 35 and 36) are significantly affected by rainfall. Statistical tests indicate misspecification in all the models estimated, but the extended models, which allow for time variation could not be estimated for the second category (basic chemical and chemical products, except products of petroleum and coal) due to highly nonlinear nature of the models involved and the relatively small sample size in comparison to that. For the other two components, the estimated models indicate that seasonality is affected by rainfall and also dynamics have undergone significant changes during the 1990s. The former finding implies that both demand and supply channels may be important in transmission of variation in rainfall to manufacturing[1].

The rest of the paper is organised as follows. The following section discusses the seasonal character of the Indian economy and the institutional changes in the Indian economy during past three decades. Section 3 describes methodology of the paper, followed by a description of data used, in Section 4. Section 5 discusses the empirical results, and Section 6 contains concluding observations.

2 Seasonal Character of the Indian Economy

2.1 Seasonal character of the economy

The Indian economy is highly seasonal. This is mainly due to the predominantly agricultural character of the economy. Though agriculture contributes less than a quarter of total output, it employs more than half of its workforce. Due to lack of sufficient irrigation facilities, the agriculture still depends heavily on rainfall. Rainfall occurs mainly in two seasons: June-September (summer) and December-February (winter). Therefore, agricultural activity is also concentrated in these two seasons only. The summer rainfall covers a larger area and therefore the crop in this season, or *Kharif* crop has slightly larger share in total agricultural output.

[1]The linkages between agriculture and industry are well-documented in the literature, for India as well as many other countries (e.g., Bhamumurthy and Sinha, 2004; Kanwar, 2000 and Suryahadi *et al.*, 2006, among others). This paper provides evidence for the same from the point of view of seasonal variation in disaggregated manufacturing production.

The winter crop, or *Rabi* crop is more dependent on irrigation facilities and therefore accounts for a lower share of total output, though of late the gap between the shares of the two has been declining. Due to high volatility of quantum as well distribution of rainfall, the crops, particularly the *Kharif* crop also shows huge fluctuations. These fluctuations affect the rest of the economy through both demand and supply linkages. Specifically, agriculture provides raw materials for a large number of industries. On the other hand, since a major part of population is dependent on agriculture for its livelihood, this sector is a major source of demand for the industrial products. Further, agricultural sector gets several inputs from the industrial sector. Therefore, fluctuations in agricultural output, caused by fluctuations in rainfall affect industrial output as well.

2.2 Seasonals in the manufacturing sector

The seasonal character of the economy is clearly reflected in the industrial production in general and in the manufacturing production in particular. The production in this sector is highly seasonal. As shown in Fig. 1, the growth of output[2] is highest in the first quarter, and lowest in the second quarter. From the intra-year low in the second quarter, it rises gradually in the third and fourth quarters. In other words, the (growth of) industrial production is lowest in the second quarter and then rises gradually, attaining its peak in the first quarter.

Another aspect of the observed seasonality is the varying nature of seasonals. The seasonals are not constant over time, as can be seen clearly in the figure. Sinha and Kumawat (2004) found statistical evidence for nonstationarity of seasonality in the overall index of industrial production. Dua and Kumawat (2005, hereafter referred to as DK) pointed out two important features of these seasonal fluctuations: first, the nonstationarity of seasonality is related to nonstationarity of trend; and second, the volatility of industrial output too varies with seasons.

[2] The graph plots the growth rates in the four quarters. This is done by running a 20-quarter (five year) rolling regression of first difference of log of IIP (multiplied by 100) in manufacturing sector on four seasonal dummies. Thus sc(i) represents the rate of growth of index of production in manufacturing sector for the i^{th} quarter.

Specifically, the volatility is more in the first two quarters (the highest and lowest activity quarters, respectively) as compared to the other two. The authors opine that both the high level and high volatility of industrial output in the first quarter are mainly due to the fact that industrial activity in the last and the first quarter is powered by the agricultural performance in the *Kharif* season. This is due to both the reasons, inputs coming from agriculture, as well as demand originating due to *Kharif* crop. While this causes production in the industrial sector to attain its intra-year peak in the first quarter, the high volatility of rainfall and therefore the *Kharif* output renders it highly volatile. The second quarter witnesses hardly any activity in the agricultural sector, and industrial activity is also low in that season. The industrial activity starts picking up in the third quarter and reaches a high level in the fourth quarter. It increases further to attain its intra-year peak in the first quarter, since the *Kharif* crop reaches the factories only towards the end of the fourth quarter. Thus, one can expect the seasonality to be more pronounced in years which have high rainfall. Kumawat (2009) found evidence in support of this line of arguments. This highlights another dimension of agriculture-industry linkages in the Indian economy.

With the evidence in favour of the seasonality in manufacturing sector being governed by the agricultural production, the next issue is the channel through which this effect comes. One way to answer this question would be to look at the output data from different sub-sectors. One can separately identify sectors which get their raw materials from agriculture, and also those for which demand can be expected to be affected substantially by fluctuations in agricultural output. In this manner, evidence from the subsectors in manufacturing sectors can throw light on the channels of effect of agriculture on manufacturing sector output.

In order to test for the effects of agricultural production on these variables, and to measure their effect, we need a model which allows for regime-switching according to values of an indicator variable. As discussed in Kumawat (2009), the smooth transition autoregression (STAR) model suggested by Terasvirta and Anderson (1992) and Terasvirta (1994) seems appropriate for this purpose. This framework has the advantages that (i) there are clearly different regimes for extreme values of the transition variables, and (ii) for those values of the transition variable which lie in between the extremes, one gets a continuum of linear combinations of the extreme regimes. The location of different regimes and the speed of transition between the extreme regimes are estimated in the model itself. Due to this feature this model allows for a large number of possibilities, e.g., abrupt transition from one extreme regime to the other at some specific value of the transition variable (which is itself estimated in the model); or extremely gradual transition from one regime to other.

2.3 Gradual changes in the character of the economy

The character of the Indian economy has been changing gradually right since the time of India's freedom from the British rule in 1947. At that time, the Indian economy was primarily an agricultural economy. Gradually, the share of agriculture in India's national output declined[3], while that of industry, and even more, that of services rose[4]. Even the character of agriculture has been changing gradually, and one important aspect of this is the decline in its dependence on rainfall, due to the increasing availability of irrigation facilities[5]. Thus, not only has the dependence of the economy on agriculture fallen, the dependence of the latter on rainfall has also fallen. Both of these have reduced the dependence of the economy on natural forces. This was supplemented (to some extent, also facilitated) by a number of measures taken by the government towards liberalization, privatization and globalisation of the economy, initiated in 1980s. These measures changed the face of the economy completely from a state-controlled closed economy to an open, market economy. Clearly such a transformation would be reflected in the dynamics of the industrial output as well.

[3]The share of agriculture in India's GDP was about 50% in 1950-51. From that level, it fell to 33% in 1980-81, 27% in 1990-91 and 16% in 2006-07.

[4]From a level of 33% in 1950-51, the share of services in India's GDP rose to 40% in 1980-81 and 44% in 1990-91. It rose sharply after that and stood at 55% in 2006-07, thus accounting for more than half of India's GDP.

[5]The share of gross irrigated area in gross cropped area rose from 23% in 1970-71 to 29% in 1980-81, 34% in 1990-91 and 41% in 2002-03.

These changes can also be accommodated in the framework of smooth transition autoregression, as discussed by, e.g., Van Dijk, Strikholm and Terasvirta (2003, henceforth referred to as VST). The following section discusses the methodology in detail.

3 Data and Methodology

3.1 The STAR model with seasonality

The simple STAR model allowing for deterministic seasonal variation is

$$y_t = (1-F(w_t))\left(\sum_{i=1}^{4}\delta_{1i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{1i}^{*}y_{t-i}\right)+F(w_t)\left(\sum_{i=1}^{4}\delta_{2i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{2i}^{*}y_{t-i}\right)+\varepsilon_t \qquad (1)$$

where $F(w_t)$ is a transition function with $F(w_t)\in[0,1]$ for $w_t\in(-\infty,\infty)$. This is a simple extension of the simple STAR model, properties of which have been discussed in detail by several authors (e.g., Terasvirta and Anderson, 1992; Terasvirta, 1994). Though this model allows for variation in deterministic seasonality with the indicator w_t, mere variation of the coefficients of seasonal dummies with variation in w_t in this model is not evidence of variation in deterministic seasonals, since the coefficients of seasonal dummies in this model can change due to change in deterministic seasonals, or the autoregressive coefficients, or both. It must be recognized that the simple AR model with seasonally varying intercepts is a reduced form of the model

$$y_t = \sum_{i=1}^{4}\delta_i D_{it}+\sum_{i=1}^{p}\phi_i z_{t-i}+\varepsilon_t \qquad (2)$$

where

$$z_t = y_t - \sum_{i=1}^{4}\delta_i D_{it}. \qquad (3)$$

It is δ_i in the model (2) which represents seasonal means, and not the seasonal intercepts in a simple AR model with seasonally varying intercepts (the latter is in fact a linear combination of the seasonal means δ_i and AR parameters ϕ_i). Testing the hypothesis of regime-switching in the seasonal component, therefore, has to be based on difference between the coefficients on seasonal dummies in the model estimated in deviations-from-seasonal-means form and not by testing for $\delta^*_{1i} = \delta^*_{2i}$, in eq. (1), as was suggested by Franses *et al.* (2000) and VST. That is, the correct way to test this hypothesis would be to estimate the model in the deviation-from-seasonal mean form, i.e.,

$$y_t = \left(\sum_{i=1}^{4} \delta_{1i} D_{it} + \sum_{i=1}^{p} \phi_{1i} z_{1t-i}\right)[1 - F(w_t)] + \left(\sum_{i=1}^{4} \delta_{2i} D_{it} + \sum_{i=1}^{p} \phi_{2i} z_{2t-i}\right) F(w_t) + \varepsilon_t \quad (4)$$

where

$$z_{kt} = y_t - \sum_{i=1}^{4} \delta_{ki} D_{it} \quad (5)$$

for $k = 1,2$, and then test for the hypothesis $\delta_{1i} = \delta_{2i}$. Simply testing the equality of coefficients in a linear model of the form (1) just shows that the parameters of the model vary with the values of the transition variables, i.e., that *the variable does respond to the transition variable*, but, in this form, do not provide sufficient evidence that *the seasonal means vary*. In fact, the coefficients of seasonal dummies in these models can change both due to changes in seasonal means and in AR parameters. While theoretically it is still possible to test for changes in seasonals using these specifications, this would involve testing highly nonlinear restrictions. The simpler way would, thus, be to estimate these models in deviations-from-seasonal-means form. This is the method used here.

3.2 Allowing for time variation

Gradual institutional and technological changes in the economy can cause the dynamics as captured by the equation (4) to change over time. If this is the case, the results from this model will show misspecification, and therefore, will not be reliable. As mentioned earlier, this type of changes can also be accommodated in the framework of smooth transition autoregression. This is done by allowing the structure in the equation (4) to have different coefficients before and after some threshold. This is achieved by introducing another transition function, with

$t^* \equiv t/T$ as the transition variable, where T is the total sample size. Thus one needs to estimate the model

$$\begin{aligned} y_t \;=\; & \left[\left(\sum_{i=1}^{4}\delta_{11i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{11i}^{*}z_{11t-i}\right)(1-F(w_t))+\left(\sum_{i=1}^{4}\delta_{21i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{21i}^{*}z_{21t-i}\right)F(w_t)\right](1-F(t^*)) \\ & \left[\left(\sum_{i=1}^{4}\delta_{12i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{12i}^{*}z_{12t-i}\right)(1-F(w_t))+\left(\sum_{i=1}^{4}\delta_{22i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{22i}^{*}z_{22t-i}\right)F(w_t)\right]F(t^*) \\ & +\varepsilon_t \end{aligned} \tag{6}$$

where

$$z_{klt} = y_t - \sum_{i=1}^{4}\delta_{kli}^{*}D_{it} \tag{7}$$

for $k,l = 1,2$

3.3 Methodology of the paper

On the basis of the discussion in the previous subsection, we proceed as follows:

1. We begin with a linear AR model with seasonally varying intercepts. The order of autoregression is determined on the basis of AIC, SIC and LM test for residual serial correlation.

2. Having determined the order of autoregression (p) in the first step, in the next step we carry out the test for nonlinearity. For this, the eq. (1) can be rewritten as

$$y_t = \left(\sum_{i=1}^{4}\delta_{1i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{1i}^{*}y_{t-i}\right)+F(w_t)\left(\sum_{i=1}^{4}\delta_{2i}^{*}D_{it}+\sum_{i=1}^{p}\phi_{2i}^{*}y_{t-i}\right)+\varepsilon_t \tag{8}$$

   The hypothesis of linearity in the equation (1) cannot be done using the standard Wald test for testing restrictions, as here parameters in the second bracket are not identified under the null hypothesis[6]. The test therefore has to be based on the Taylor series expansion of the transition function. Replacing the transition function in the above equation by its

[6]This issue has been discussed in detail in the literature, e.g., Terasvirta and Anderson (1992) and Terasvirta (1994, 2004).

third-order Taylor series expansion, we get

$$y_t = \left(\sum_{i=1}^{4} \delta_{1i}^{**} D_{it} + \sum_{i=1}^{p} \phi_{1i}^{**} y_{t-i} \right) + \sum_{j=1}^{3} \left(\sum_{i=1}^{4} \delta_{2i}^{**} D_{it} + \sum_{i=1}^{p} \phi_{2i}^{**} y_{t-i} \right) w_t^j + \varepsilon_t \tag{9}$$

The test for nonlinearity can be carried out in large samples using LM-type test for significance of the cross product terms[7]. For better size, the corresponding F-statistic is preferred.

3. In the next step we estimate the STAR model (eq. 4) for the transition variables suggested by the test for non-linearity. We estimate the model using first and second order logistic functions as the transition function, given by

$$F(w_t) = F(w_t; \gamma, \mu) = \frac{1}{1 + \exp(-\gamma(w_t - \mu))}, \tag{10}$$

and

$$F(w_t) = F(w_t; \gamma, \mu_1, \mu_2) = \frac{1}{1 + \exp(-\gamma(w_t - \mu_1)(w_t - \mu_2))}, \tag{11}$$

respectively. The difference between the two is that while the first-order logistic function is monotonic in w_t and therefore allows for only two-regimes, those corresponding to low values and high values; value of the second order function first declines with rise in the value of the transition variable, attains a minimum for some middle value of the transition variable and rises again thereafter, thus allowing for three regimes.

4. Before testing for changes in seasonality, these models need to be tested for misspecification. In addition to standard tests for normality of residuals and tests for autocorrelation (first and fourth order), we also test for time variation in the coefficients. The tests for autocorrelation and time variation are derived along the lines suggested by Eitrheim and Terasvirta (1996).

[7] See, e.g., Terasvirta (2004).

5. If these tests indicate misspecification, the models are to be extended. Due to small sample available, we consider only one extension, namely, allowing for time variation. Therefore, we estimate the model (6).

6. Finally we test for variation in seasonal dynamics. This can be done by simply testing for equality of coefficients of seasonal dummies in different regimes. Given that there are four distinct regimes in this model, one can test four types of hypotheses. For instance, in order to test whether the rainfall affected the seasonality before the institutional changes in the economy, one needs to test for the hypothesis $\delta^*_{11i} = \delta^*_{21i}$, for testing whether this is true now, the hypothesis would be $\delta^*_{12i} = \delta^*_{22i}$. Similarly, to test whether the seasonality in the regime characterised by low value of w_t has undergone significant changes over time, one needs to test for $\delta^*_{11i} = \delta^*_{12i}$, the corresponding hypothesis for the regime characterised by high value of w_t would be $\delta^*_{21i} = \delta^*_{22i}$.

4 Data

4.1 Output variables

For this exercise we have selected those sectors which have more than 10% weightage in the Index of Industrial Production (IIP) for the manufacturing sector. Since the weightage of manufacturing in the General IIP is 793.58, we selected three subsectors: Food products (2-digit classification code 20-21), Basic chemicals and chemical products (except products of petroleum and coal, code 30) and manufacture of machinery and equipment other than transport equipment (code 35-36). The details of these are given in Table 1 and these variables have been referred to as $IIP2021$, $IIP30$ and $IIP3536$, respectively. We have taken quarterly growth rates of IIP in each of these three subsectors, calculated as first difference of log IIP in the respective sector. We have considered quarterly data from 1981q1 through 2008q4. The data have been taken from the website of the Central Statistical Organisation (CSO), Government of India.

4.2 Indicators of agriculture

As discussed above, the agriculture is affected heavily by rainfall. Further, at quarterly frequency no other reliable indicator of agricultural production is available. As indicator of rainfall, we have taken four variables: two indicators of deviation from normal and two indicators related to actual level of rainfall. In indicators of deviation from normal, we have taken deviation from normal rainfall[8] (DEV_t), and deviation from normal rainfall as percentage of normal rainfall ($DEVPC_t$). The other two indicators are, total rainfall in the year ending in the quarter concerned (denoted by ART_t) and annual growth rate of rainfall in the quarter concerned (denoted by $AGRR_t$). Data for rainfall have been taken from *www.indiastat.com* and various issues of the Monthly Review from the Centre for Monitoring the Indian Economy (CMIE).

5 Empirical Results

A preliminary idea about the variation in seasonal fluctuations in the components of IIP can be had from the plots. Fig. 2 through 4 show the variation in seasonal fluctuations in the three components of IIP analysed here. These figures show 5-year average seasonal means for quarterly growth of the different series. These are obtained by rolling regression of the respective quarterly rate of growth on the four seasonal dummies. Thus, the line $sc(i)$ shows the seasonal mean for i^{th} quarter. The plots clearly show substantial variation in seasonal fluctuations in all the series.

Before coming to results of tests and estimation, one note about the specification of the deterministic seasonal component in equations discussed above. We specify the seasonal dummies as $D_{it} = S_{it} - S_{1t}, \quad i = 2,3,4$; and D_{1t} as intercept, where S_{it} takes value 1 in the i^{th} quarter and zero otherwise. The advantage of using this approach is the coefficients on D_{it} for $i = 2,3,4$ give us the deviations of means for the respective quarters from the average intercept.

[8] Normal rainfall for a given quarter is calculated as 10-year moving average of actual rainfall in that quarter.

The corresponding deviation for the first quarter is calculated as (-1) times sum of coefficients for the other three quarters. Thus the coefficient represents actual seasonal and not total rate of growth in any season, which could be high/low due to rise/decline in overall growth also.

In the first step of the estimation for testing, the order of autoregression was determined for each series. The order of autoregression as well as the variables for which the variables showed statistically significant non-linearity are given in Table 2.

These results show clearly that the rainfall does affect the dynamics of industrial production in all the three subsectors studied here. The strongest evidence comes for IIP 3536, for which the test $p-$ values are less than 0.05 for all but a few combinations.

However, as discussed above, this result in itself does not tell us whether it affects the seasonal component or the non-seasonal component, and in order to answer this question, we need to estimate the model in deviations-from-seasonal-mean form. Therefore, the equation (eq. 4) was estimated for all the variables mentioned against the variables in the Table 2. Both the transition functions mentioned above, viz., first and second order logistic function were tried. In some cases, estimation was not possible due to numerical problems. In some other cases, the coefficients had very weird values, e.g., the seasonal dummies having coefficients of order of thousands, again reflecting numerical problems. The remaining models were then subjected to standard misspecifications checks: normality of residuals, autocorrelation (first and fourth order) and time variation in coefficients. The tests for autocorrelation and time variation were derived along the lines suggested by Eitrheim and Terasvirta (1996). The results showed that almost all the models showed some form of misspecification or other. This means that the coefficients from these models cannot be relied upon and the models need to be extended. Given the large number of parameters to be estimated in the estimated model and consequent small number of degree of freedom left, we considered only one type of extension here, allowing for time variation. This extension is also highly plausible in view of the gradual institutional changes in the Indian economy discussed in Section 2.3. Again numerical problems of the type discussed above cropped up, and not many models could be estimated. At this stage we cannot run the test for autocorrelation and remaining non-linearity due to extremely small number of degrees of freedom one would be left with for these tests, rendering these tests unreliable. We looked only at the test for normality, and discarded the models for which the assumption of normality of residuals was rejected at 5% or smaller levels of significance. The rest of the models were tested for effect of rainfall and time on the seasonality. Out of the three variables considered here, we could not estimate properly any model for IIP30. For the other two variables, estimation results alongwith the test results are presented in tables. Table 3 to 6 contain results for IIP2021 while the rest of tables, namely 7 to 22 present results for IIP3536. For each indicator we give two types of results: one, the seasonal components in the four regimes and two, the changes in seasonal components with the indicator of rainfall and time.

Since so many indicators have been found to affect the dynamics of these variables, we do not try to choose a single model for each variable. Instead, we report all the models satisfying the aforementioned criteria, to assess whether the rainfall indicators and time affect the seasonal dynamics at all.

The results presented in Table 6 provide evidence of both rainfall and time affecting the seasonality in IIP2021, though the results in table 5 indicate only mild seasonality in this variable. These effects are more substantial in IIP3536, as can be seen from tables 7 to 22. Another point to note is that the transition point estimated lies between 0.40 and 0.55, which, given an overall sample size of 112 means periods 45 and 62. Since the sample begins in 1981q1, it means periods 1992q1 and 1996q2, indicating the turning points with respect to the institutional changes are concentrated in the first half of 1990s approximately.

6 Concluding Observations

In this paper an attempt has been made to investigate the channel through which the rainfall affects the seasonals in manufacturing production. This is sought to be done by testing for effect of rainfall on manufacturing production in three sub-sectors of manufacturing sector, having more than 10 % weightage in overall index of manufacturing. The results show clear evidence of seasonals in production in the food products and machinery and equipment (other than transport equipment) being affected by rainfall. Further, we also find evidence of effect of gradual institutional changes in the Indian economy on seasonality in these variables. The highly nonlinear nature of models estimated and small size of sample in comparison led to numerical problems in estimation, preventing us from estimating many models. Due to this we could not estimate the models for production in basic chemicals and chemicals products. Nevertheless, the results of this paper provide some evidence that the rainfall affects the seasonals in manufacturing production through both demand and supply channels, and also that this effect is changing with time, due to gradual institutional changes in the economy.

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Table 1: Details of components of IIP manufacturing taken

2-Digit Classification Code	Description	Weightage in IIP	Relative Weightage in IIP manufacturing(%)	Link with agriculture
20-21	Food Products	90.83	114.46	Raw materials from agriculture
30	Basic chemicals and chemical products except products of petroleum and coal	140.02	176.44	Demand from agriculture: consumption and investment
35-36	Manufacture of machinery and equipment other than transport equipment	95.65	120.53	Demand from agriculture: consumption and investment

Table 2: Tests for nonlinearity

Series[a]	p[b]	Indicator	p-value
IIP2021	3	$AGRR_{t-2}$	6.0809×10^{-4}
		ART_{t-3}	0.0363
IIP30	2	ART_t	0.0213
IIP3536	6	DEV_t	0.0086
		DEV_{t-1}	0.0396
		DEV_{t-2}	0.0195
		DEV_{t-3}	0.0318
		DEV_{t-4}	0.0142
		$DEVPC_t$	0.0105
		$DEVPC_{t-1}$	0.0432
		$DEVPC_{t-2}$	0.0202
		$DEVPC_{t-3}$	0.0329
		$DEVPC_{t-4}$	0.0168
		ART_t	0.0024
		ART_{t-2}	0.0136
		ART_{t-3}	0.0099
		ART_{t-4}	0.0087
		$AGRR_t$	0.0202

[a] As discussed earlier, each series was taken in the form of first difference of log.

[b] Order of autoregression.

Results for IIP2021

Table 3: Estimation results: Second order function, $AGRR_{t-2}$ as transition variable

Quarter	Pre-transition regime[a]				Post-Transition regime			
	Low-value regime[b]		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	0.0251	0.8732	0.0107	0.9179	0.0486	0.8261	8.7824	0.0041
II	-0.2173	0.9971	-1.9999	0.5072	-2.8397	0.5039	-8.1450	0.8825
III	-34.7993	0.8786	-5.7481	0.3948	0.0186	0.9995	-5.7481	0.3948
IV	-9.8194	0.3085	1.3121	0.6454	0.5793	0.9269	5.9093	0.8977
γ_w								147.0958
μ_{w1}								-13.7679
μ_{w2}								31.3773
γ_t								30.6026
μ_t								0.5259

[a] The pre-transition and post-transition regimes refer to the periods corresponding to $t^* \to 0$ and $t^* \to 1$, respectively.

[b] The low-value and high-value regimes are the regimes corresponding to $w_t \to -\infty$ and $w_t \to +\infty$, respectively.

Table 4: Test results for changes in seasonals: Second order function, $AGRR_{t-2}$ as transition variable

Quarter	Change with $AGRR_{t-2}$				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	0.0230	0.8798	0.0295	0.8640	0.0249	0.8751	0.0144	0.9047
II	0.0034	0.9539	2.7479	0.1016	6.667×10^{-5}	0.9935	0.0221	0.8822
III	0.0227	0.8807	0.1078	0.7436	0.0211	0.8850	0.2218	0.6390
IV	1.3929	0.2417	0.0552	0.8148	0.6054	0.4389	0.0796	0.7786

Table 5: Estimation results: First order function, $AGRR_{t-3}$ as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	1.6708	0.2001	0.2877	0.5933	3.3694	0.0704	0.8032	0.3729
II	3.8931	0.3902	-8.5269	0.3480	-3.6952	0.3983	-7.6875	0.1068
III	-6.0578	0.2089	-30.0122	0.0362	-7.8563	0.0598	6.3279	0.2099
IV	3.5079	0.4405	1.5183	0.8350	0.7892	0.8464	3.1713	0.3784
γ_w								2.369×10^{18}
μ_w								4.7830
γ_t								691.5069
μ_t								0.5089

Table 6: Test results for changes in seasonals: First order function, $AGRR_{t-3}$ as transition variable

Quarter	Change with $AGRR_{t-2}$				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	1.7777	0.1865	3.1712	0.0.0790	2.1653	0.1453	3.6148	0.0611
II	1.5077	0.2233	2.2696	0.1316	1.3520	0.2486	0.9841	0.3244
III	1.2917	0.2594	0.8061	0.3722	0.0584	0.8097	1.6056	0.2090
IV	0.8964	0.3468	4.4363	0.0.0365	5.1410	0.0262	10.2565	0.0020

Results for IIP3536

Table 7: Estimation results: First order function, DEV_t as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	3.6581	0.0606	6.3794	0.0142	0.2253	0.6368	0.9269	0.3395
II	-7.2163	0.0029	-5.8088	0.4930	-4.8447	0.2060	-6.8137	0.1493
III	0.3241	0.8441	-16.4710	0.3511	0.4279	0.8682	2.7410	0.4495
IV	4.1581	0.0436	10.7634	0.4715	2.6341	0.3542	-0.8200	0.7944
γ_w								12.5435
μ_w								2.2452
γ_t								1.284×10^{12}
μ_t								0.4093

Table 8: Test results for changes in seasonals: First order function, DEV_t as transition variable

Quarter	Change with DEV_t				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	1.3623	0.2476	0.2661	0.6078	0.4161	0.5214	0.2919	0.5910
II	8.3070	0.0055	0.4649	0.4979	1.4288	0.2367	9.1180	0.0037
III	0.3621	0.5496	15.6200	0.0002	2.6488	0.1089	0.2386	0.6270
IV	4.4639	0.0388	1.7127	01956	4.6621	0.0348	1.7104	0.1959

Table 9: Estimation results: First order function, DEV_{t-1} as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	4.4997	0.0380	0.4221	0.5184	6.1812×10^{-4}	0.9802	4.0232	0.0494
II	-1.8784	0.3848	-6.8427	0.0595	-5.4007	0.4387	-5.1770	0.1371
III	-2.7462	0.1560	2.9180	0.3030	-2.2631	0.6426	0.7708	0.8072
IV	0.5102	0.8338	2.0300	0.5869	4.8052	0.3903	-0.3674	0.8890
γ_w								2429.8653
μ_w								-19.0556
γ_t								95018.9542
μ_t								0.4281

Table 10: Test results for changes in seasonals: First order function, DEV_{t-1} as transition variable

Quarter	Change with DEV_{t-1}				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	2.6556	0.1084	0.0372	0.8478	0.5429	0.4641	0.0087	0.9259
II	0.6825	0.4120	0.2234	0.6382	0.8297	0.3660	0.1214	0.2939
III	1.3380	0.2520	23.4995	0.0000	8.0151	0.0063	0.0555	0.8146
IV	0.0792	0.7793	1.6176	0.2083	1.8310	0.1811	1.4325	0.2361

Table 11: Estimation results: Second order function, DEV_{t-1} as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	16.4840	0.0001	0.0781	0.7808	1.7531	0.1906	1.0886	0.3010
II	0.5936	0.7236	1.5196	0.4716	-7.3802	0.1742	-1.8901	0.6144
III	-8.8215	0.0039	0.9349	0.6409	-0.9468	0.8095	2.7607	0.5004
IV	-0.0507	0.9746	-6.8189	0.0548	1.3894	0.6997	-0.4982	0.9013
γ_w								268.1527
μ_{w1}								-89.8053
μ_{w2}								100.9592
γ_t								619.9316
μ_t								0.4284

Table 12: Test results for changes in seasonals: Second order function, DEV_{t-1} as transition variable

Quarter	Change with DEV_{t-1}				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	12.1647	0.0009	1.3853	0.2439	0.0599	0.8075	1.8142	0.1832
II	0.0768	0.7826	3.9532	0.0514	3.6813	0.0597	0.3231	0.5719
III	8.7624	0.0044	4.0491	0.0488	11.6569	0.0012	0.3684	0.5462
IV	0.0135	0.9080	0.1049	0.7471	0.2059	0.6517	5.8761	0.0184

Table 13: Estimation results: Second order function, DEV_{t-2} as transition function

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	5.2042	0.0262	0.0310	0.8609	0.4192	0.5199	1.2845	0.2616
II	-0.10	0.9693	-7.27	0.0019	-8.47	0.1116	-4.42	0.4534
III	-0.39	0.8597	-0.56	0.7446	1.95	0.6101	4.09	0.5058
IV	-7.57	0.0026	5.63	0.0062	2.91	0.4243	0.34	0.9241
γ_w								538.03
μ_{w1}								-105.28
μ_{w2}								97.76
γ_t								3908854.20
μ_t								0.43

Table 14: Test results for changes in seasonals: Second order function, DEV_{t-2} as transition function

Quarter	Change with DEV_{t-2}				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	4.7644	0.0330	0.5880	0.4463	2.9644	0.0906	0.4009	0.5291
II	0.0055	0.9414	8.5155	0.0050	3.1631	0.0805	0.1081	0.7434
III	0.0895	0.7659	3.2745	0.0755	1.3298	0.2535	0.4530	0.5036
IV	10.0664	0.0024	0.4389	0.5103	0.2486	0.6199	4.6838	0.0345

Table 15: Estimation results: Second order function, $DEVPC_{t-2}$ as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	0.8661	0.3558	0.0081	0.9285	0.0347	0.8529	0.1121	0.7390
II	-0.0983	0.9837	-7.2729	0.0534	-8.4691	0.2540	-4.4173	0.8624
III	-0.3924	0.8720	-0.5649	0.8780	1.9526	0.7782	4.0861	0.8603
IV	-7.5727	0.5058	5.6294	0.0120	2.9091	0.7396	0.3441	0.9246
γ_w								4871.4540
μ_{w1}								-9.8230
μ_{w2}								9.0233
γ_t								4.8812×10^{13}
μ_t								0.4260

Table 16: Test results for changes in seasonals: Second order function, $DEVPC_{t-2}$ as transition variable

Quarter	Change with $DEVPC_{t-2}$				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	0.7497	0.3901	0.0577	0.8109	0.7535	0.3889	0.0312	0.8604
II	0.0021	0.9640	3.3532	0.0721	1.7048	0.1967	0.0049	0.9444
III	0611	0.8056	0.4037	0.5277	0.2936	0.5900	0.1929	0.6621
IV	0.4840	0.4894	0.0242	0.8768	0.0441	0.8345	3.3603	0.0718

Table 17: Estimation results: First order function, $DEVPC_{t-4}$ as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	6.1187	0.0162	0.4178	0.5205	0.1979	0.6581	7.9317	0.0066
II	-1.3923	0.5650	2.2084	0.2697	-5.8691	0.0503	-3.6913	0.4718
III	-1.6665	0.4489	1.1860	0.4798	2.7157	0.1955	3.7677	0.4819
IV	-2.8215	0.2376	-2.0311	0.1837	2.2485	0.2323	-5.6553	0.4136
γ_w								4.5449
μ_w								3.4799
γ_t								1119.9639
μ_t								0.4015

Table 18: Test results for changes in seasonals: First order function, $DEVPC_{t-4}$ as transition variable

Quarter	Change with $DEVPC_{t-4}$				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	6.2746	0.0150	0.1012	0.7515	0.3749	0.5427	0.2446	0.6227
II	0.2342	0.6302	0.8851	0.3506	0.0518	0.8208	0.0023	0.9622
III	0.9305	0.3386	17.3006	0.0001	4.5617	0.0368	14.0100	0.0004
IV	1.3960	0.2421	0.3930	0.5331	0.0235	0.8787	0.2777	0.6002

Table 19: Estimation results: First order function, ART_t as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	3.6989	0.0592	2.3967	0.1269	0.0355	0.8512	1.1286	0.2923
II	-3.2459	0.1127	-3.0096	0.4353	-4.9765	0.2541	-5.5193	0.1114
III	-2.9371	0.0901	-9.5603	0.1828	0.2519	0.9307	1.9001	0.4636
IV	3.7052	0.0392	1.2763	0.8327	2.3988	0.4167	-0.5638	0.8092
γ_w								205.2790
μ_w								-1037.8635
γ_t								5.1610×10^{25}
μ_t								0.4052

Table 20: Test results for changes in seasonals: First order function, ART_t as transition variable

Quarter	Change with ART_t				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	1.7593	0.1897	0.0157	0.9007	0.0276	0.8686	0.0076	0.9308
II	2.5808	0.1134	0.0166	0.8979	0.5078	0.4789	2.4712	0.1212
III	1.7296	0.1935	21.7657	0.0000	10.3132	0.0021	1.0176	0.3171
IV	4.5652	0.0367	2.0302	0.1594	5.7661	0.0195	2.1778	0.1452

Table 21: Estimation results: First order function, $AGRR_t$ as transition variable

Quarter	Pre-transition regime				Post-transition regime			
	Low-value regime		High-value regime		Low-value regime		High-value regime	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
I	1.5461	0.2186	0.2749	0.6020	1.0438	0.3110	14.0164	0.0004
II	-12.0708	0.5475	-5.4062	0.0258	-1.6973	0.7888	-12.5236	0.2241
III	5.0448	0.5292	-2.0987	0.1846	2.8789	0.7548	-12.5236	0.2241
IV	-12.9702	0.3673	0.0002	0.9992	0.1995	0.9815	3.3557	0.4786
γ_w								9628.929
μ_w								-13.7982
γ_t								1.0985×10^{42}
μ_t								0.4062

Table 22: Test results for changes in seasonals: First order function, $AGRR_t$ as transition variable

Quarter	Change with $AGRR_t$				Change with time			
	Pre-transition regime		Post-transition regime		Low-value regime		High-value regime	
	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val	statistic	$p-$ val
I	1.399	0.2414	0.7305	0.3961	0.2586	0.6130	0.9133	0.3431
II	0.283	0.5933	0.3847	0.5375	0.3637	0.5487	0.0083	0.9276
III	0.3713	0.5446	3.4530	0.0680	0.1255	0.7244	0.2360	0.6289
IV	0.8681	0.3552	1.4040	0.2407	6.4806×10^{-4}	0.9798	2.0652	0.1559

Figures

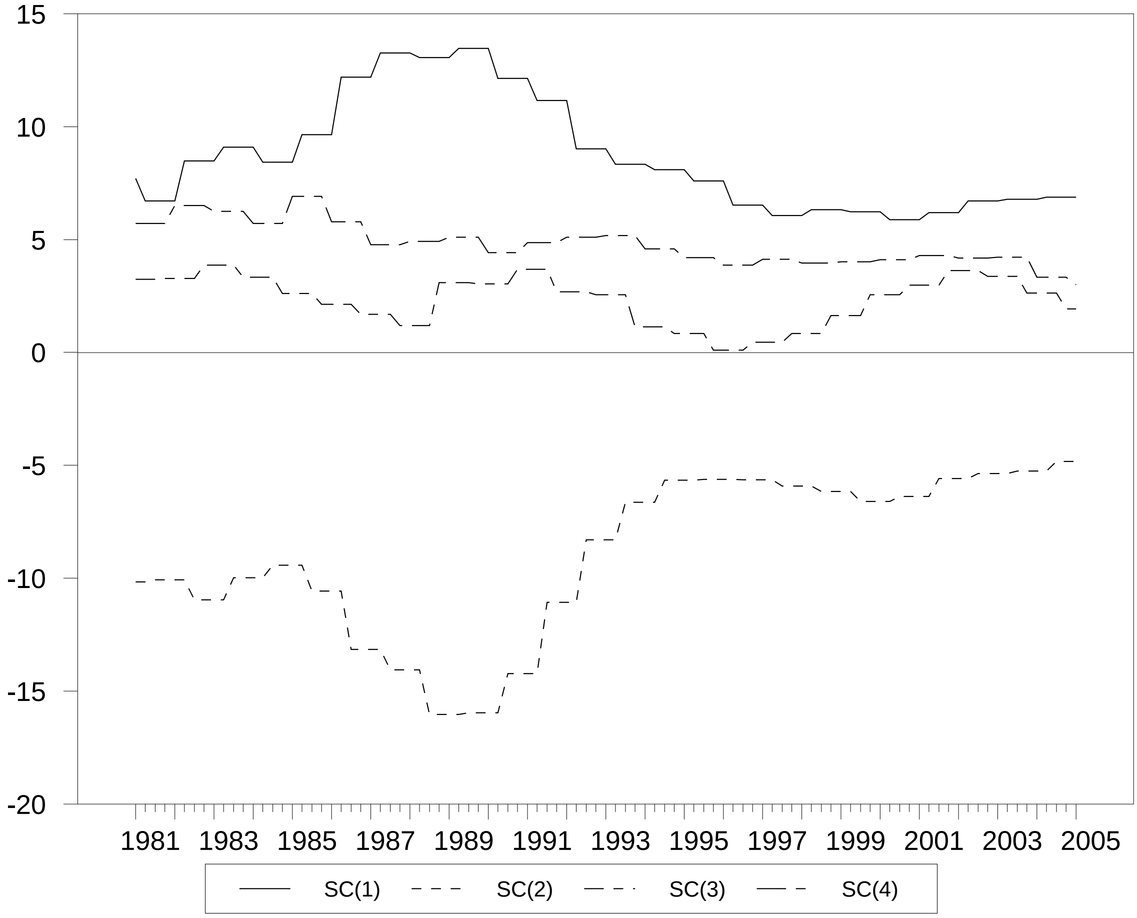

Figure 1: Evolution of Seasonals in IIP in Manufacturing Sector in the Indian economy

Notes:

1. The value for a given quarter represents sample mean of first differenced log IIP in that quarter during that period, thus giving the quarterly growth rate of IIP in that quarter.
2. These were calculated by running the rolling regression of first differenced log IIP on four seasonal dummies. The window size was 20 (implying that each coefficient gives average

growth rate of first differenced log IIP in that period for *five* years) and the points on the time axis correspond to the first point in the window. Thus, for instance, a value shown here against 1991q1 is for the period 1991q1-1995q4.

Figure 2: Evolution of Seasonals in IIP in Food products subsector of Manufacturing Sector in the Indian economy

Figure 3: Evolution of Seasonals in IIP in Basic chemicals and chemical products (except coal and petroleum products) subsector of Manufacturing Sector in the Indian economy

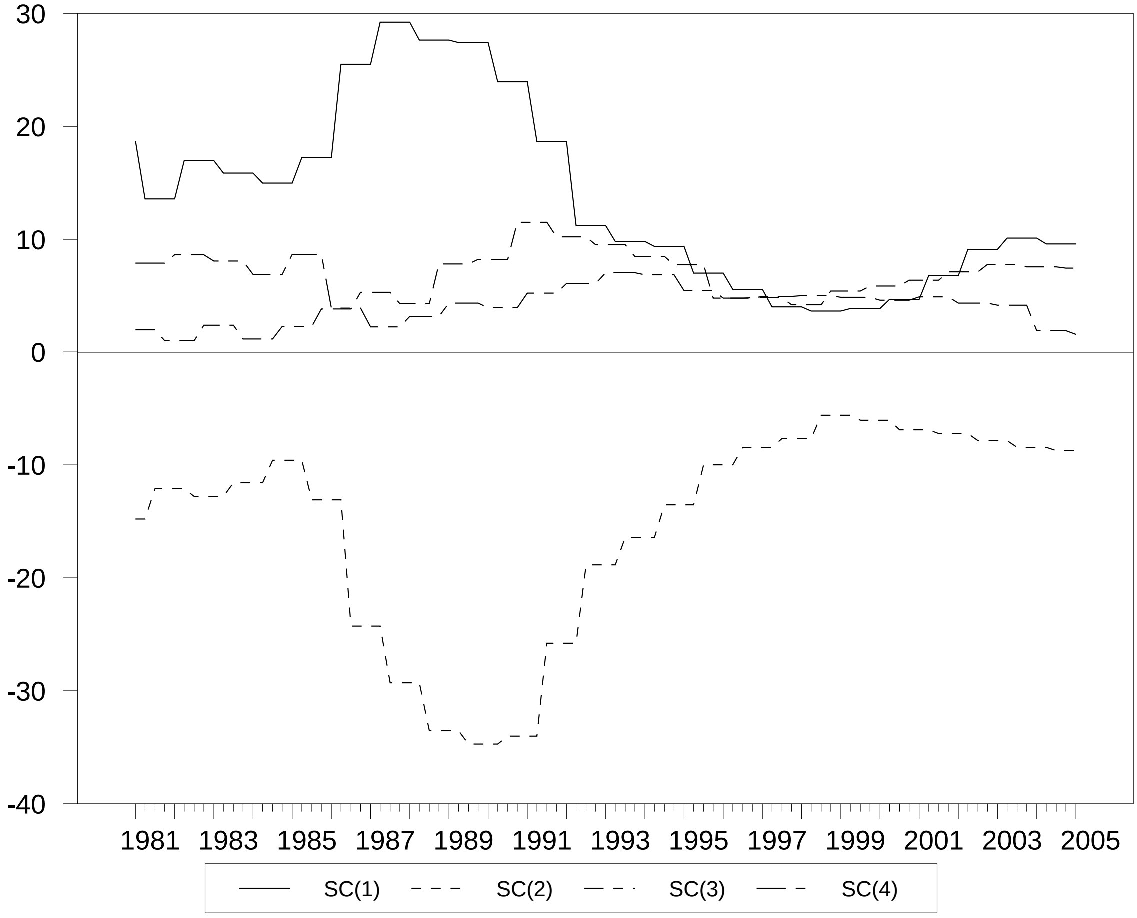

Figure 4: Evolution of Seasonals in IIP in Machinery and equipment (other than transport equipment) subsector of Manufacturing Sector in the Indian economy