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Modelling Seasonal Dynamics in Indian Industrial Production: An Extention of TV-STAR Model

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Abstract

This paper models the seasonal dynamics in quarterly industrial production for India. For this, we extend the time-varying smooth transition autoregression (TV-STAR) model to allow for independent regime-switching behaviour in the deterministic seasonal and cyclical components. This yields the time-varying seasonal smooth transition (TV-SEASTAR) model. We find evidence of the effect of rainfall growth on seasonal dynamics of industrial production. We also find that the seasonal dynamics have changed over the past decade, one aspect of this being the significant narrowing down of seasonals. The timing of these changes coincides with the changes in the character of the economy as it progressed towards a free-market economy in the post liberalization period.

JEL Classification Code: C22

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1 Introduction

Seasonality is an important component of industrial output in many countries, and at times swamps other movements. However, until recently, seasonality was considered to be very regular and therefore devoid of any economic information. This led to the practice of seasonal adjustment before the series was used for further analysis. Since it has now been recognized that seasonal fluctuations are not very regular and may contain important information about the economy, attempts have been made to model seasonality in output.

Seasonality has special relevance to the Indian economy due to the predominant role of agriculture in the economy. Though agriculture contributes only 24% to total output, it accounts for 60% of the total labour force that depend on agriculture for their livelihood. Due to the lack of irrigation facilities, the agriculture depends heavily on rainfall, the bulk of which comes in two seasons: June-September and December-February. This dependence on rainfall imparts to agriculture a high degree of seasonality. Thus, any activity which has strong linkages with agriculture, including industrial production, is also expected to be seasonal.

Attempts to study the dynamics of Indian industrial production at the sub-annual frequency have shown that it has a high degree of seasonality, but that seasonality varies over time. While Sinha and Kumawat (2004) have shown that seasonality in output is stochastic, Dua and Kumawat (2005) show that besides being stochastic, it is also related to the stochastic trend. The latter study also finds that industrial production is much more volatile in the first two quarters of the calender year, which correspond to highest and lowest industrial production respectively, as compared to the last two. The authors suggest that this is due to the fact that industrial production is related to agricultural production. This in turn, depends heavily on rainfall, which is highly volatile. Therefore, agricultural production is also very volatile and this causes high volatiilty in industrial output as well.

van Dijk *et. al* (2001, VST henceforth) identify two types of changes in seasonals: cyclical changes caused by the stage of the business cycle, and secular changes caused by gradual institutional and technological changes. For the Indian economy, the cyclical changes are influenced both by the stage of the business cycle as well as the performance of agriculture, which, in turn, depends on rainfall. Similarly, the secular change caused by technological and institutional changes also appear to be important, particularly in view of the substantial marked-oriented reforms introduced in the early 1990s. Thus, the framework adopted by VST appears to be relevant here as well, after making allowance for the variation due to rainfall.

The objective of this paper is to model the seasonal dynamics of industrial production in the Indian economy. Specifically, we consider two types of factors. First, we test for the effects of agricultural performance and the stage of the business cycle on the seasonals to extend the results of Dua and Kumawat (2005) that show that the seasonality in Indian industrial production is caused by the agricultural cycle and is affected by rainfall and the stage of business cycle. Next, we test whether this has been changing over time, particularly after the market-oriented reforms introduced in early 1990s. Though this fits largely in the framework of VST, we estimate a more general model. In contrast to VST's model, our model allows for independent regime-switching behaviour in the deterministic seasonal and cyclical components, and then smooth time variation in this behaviour itself. Thus, our model nests both the seasonal STAR (SEASTAR) model of Franses *et. al* (2000) and the time-varying STAR (TV-STAR) model of VST, and can therefore be called the time-varying seasonal STAR (TV-SEASTAR) model.

We find that the seasonals in the industrial production are driven mainly by the rate of growth of rainfall and that of an indicator of economic activity to capture the stage of the business cycle. This is measured by the annual growth in the industrial production. However, in the past one decade, while seasonals appear to have stabilised substantially, their character has changed.

The paper is organised as follows: the following section contains some discussion about the Indian economy. It starts with a discussion of the seasonal character of the Indian economy and the literature pertaining to that. This is followed by a brief discussion of gradual changes in the character of the economy. Section 3 discusses the basic smooth transition autoregression and its extension proposed by us, viz., the TV-SEASTAR model. Section 4 discusses the methodology of this paper, followed by the discussion of data. Section 5 presents the empirical results. Section 6 concludes.

2 Salient characteristics of the Indian economy

2.1 Seasonal Character of the Indian economy and industrial production

The Indian economy is highly seasonal. This is mainly due to the predominantly agricultural character of the economy. Though agriculture contributes only 24% of total output, it employs more than 60% of its workforce. Due to the lack of irrigation facilities, agriculture depends heavily on rainfall. Rainfall occurs mainly in two seasons: June-September (summer season) and December-February (winter season). Therefore, agricultural activity is also concentrated in these two seasons only. The summer rainfall covers a larger area and therefore the crop taken in this season, called the Kharif crop, has a larger share in total agricultural output. The other crop, called the Rabi crop is more dependent on irrigation facilities and has a lower share, though of late the gap between the two has been declining. Due to the high volatility of the quantum as well as the distribution of rainfall, the crops, particularly the Kharif crop also shows huge fluctuations. These fluctuations affect the rest of the economy through both forward and backward linkages. Specifically, agriculture provides raw materials for a large number of industries. On the other hand, as a major part of the population is dependent on agriculture for its livelihood, this sector is a significant source of demand for industrial products. Thus, agriculture plays a dominant role in shaping the seasonal as well as other fluctuations in the industrial production. Therefore industrial production is influenced heavily by the timing as well as the variation in rainfall.

The above is clearly reflected in the highly seasonal nature of industrial production. The first quarter is the highest industrial activity quarter, while the second quarter corresponds to the lowest level of industrial output. The industrial activity then rises gradually in the third and fourth quarters. In other words, the industrial production is lowest in the second quarter and then rises gradually, attaining its peak in the first quarter.

Further, the seasonals are not constant over time. Sinha and Kumawat (2004) found statistical evidence for nonstationarity of seasonality. Dua and Kumawat (2005) note two important features of these seasonal fluctuations: first, stochastic seasonality is not independent of stochastic trend; and second, the volatility of industrial output too varies with seasons. Specifically, the volatility is more in the first two quarters as compared to the last two. The authors opine that the reasons for the high level as well as the high volatility of industrial output in the first quarter is 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 inputs for the industrial sector coming from agriculture, as well as the demand originating for the industral sector in the agriculture sector due to the Kharif crop. While this causes the industrial production 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 does not witness any activity in the agricultural sector, and therefore industrial activity is also low in that season.

2.2 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[1], while that of industry, and even more, that of services rose[2]. 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[3]. 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, starting in 1991. 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.

The above discussion suggests that both types of changes in the seasonality suggested by VST appear to be important for the Indian economy. On the one hand, seasonals appear to be affected by the growth of rainfall and that of economic activity. On the other hand, there is a possibility of this pattern having changed in the past few years. Therefore, the seasonals can be modeled in the framework of the time-varying smooth transition autoregression suggested by VST.

[1] 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.

[2] 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.

[3] 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.

3 Smooth Transition Autoregression and its extensions

3.1 Basic STAR Model

We begin with an AR model with seasonally varying intercepts,

$$y_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i S_{it} + \sum_{i=1}^{p} \beta_i y_{t-i} + \epsilon_t \tag{1}$$

where $S_{it} = D_{it} - D_{1t}$, D_{it} being a seasonal dummy that takes the value 1 in the i^{th} season and 0 otherwise[4]. To allow for smooth transition in the seasonal and cyclical components according to a transition function $F(x_t, \gamma, \mu)$ whose value varies smoothly between 0 and 1 as the variable x varies in the interval $(-\infty, \infty)$, we get an extension of the smooth transition autoregression (STAR) suggested by Terasvirta and Anderson (1992). Specifically, if we choose this function (transition function) to be a logistic function[5]

$$F(x_t, \gamma, \mu) = \frac{1}{1 + \exp\{-\gamma(x_t - \mu)\}}, \quad \gamma > 0, \tag{2}$$

we get an extension of the the logistic STAR (LSTAR) model. Allowing for separate transition functions, $F_s(x_{st}, \gamma_s, \mu_s)$ and $F_c(x_{ct}, \gamma_c, \mu_c)$ for the seasonal part and cyclical parts respectively, we obtain the SEASTAR model of Franses and van Dijk (2000):

$$\begin{aligned} y_t &= \left(\sum_{i=1}^{4} \alpha_{0i} S_{it}\right)(1 - F_s(x_{st}, \gamma_s, \mu_s)) + \left(\sum_{i=1}^{4} \alpha_{1i} S_{it}\right) F_s(x_{st}, \gamma_s, \mu_s) \\ &\quad + \left(\sum_{i=1}^{p} \beta_{0i} y_{t-i}\right)(1 - F_c(x_{ct}, \gamma_c, \mu_c)) + \left(\sum_{i=1}^{p} \beta_{1i} y_{t-i}\right) F_c(x_{ct}, \gamma_c, \mu_c) + \epsilon_t \end{aligned} \tag{3}$$

where we have written S_{1t} for intercept for brevity of notation. Looking at the seasonal component, for instance, for very low values of x_{st}, $F_s(x_{st}, \gamma_s, \mu_s)$ is equal to zero, so that the coefficient of S_{it} is α_{0i}. On the other hand, for sufficiently large values of x_{st}, the value of $F_s(x_{st}, \gamma_s, \mu_s)$ is equal to unity, so that the coefficient of S_{it} is equal to α_{1i}. In between, as the value of x_{st} varies from very low to very high, the value of the transition function varies from 0 to 1. The coefficient of S_{it} is a weighted sum of the two values α_{0i} and α_{1i}, the weight depending on the value of x_{st} and also the two parameters γ_s and μ_s, called smoothness and location parameter, respectively. The smoothness parameter governs the speed of transition; for very high values of γ_s the transition function changes its value from 0 to 1 abruptly, as the x_{st} crosses the value of the location parameter. On

[4]We take these dummies instead of taking D_{it} since in this specification the coefficients denote deviations of seasons from the average intercept. Thus seasonal patterns can be seen directly from the coefficient values. The corresponding value for the first season is equal to $-(\alpha_2 + \alpha_3 + \alpha_4)$.

[5]The properties of this function have been documented extensively, and therefore are not being discussed here. See, for example, Terasvirta and Anderson (1992) and Terasvirta (1994).

the other hand, for low values of γ_s, $F_s(x_{st}, \gamma_s, \mu_s)$ changes values slowly from 0 to 1; the smaller is the value of γ_s, the slower is the transition.

Though the above specification shows clearly the values of different coefficients in different regimes, it does not show which coefficients undergo regime-switching; for that we have to test the significance of the difference between α_{0i} and α_{1i} separately for each coefficient. Therefore, we modify the specification slightly to get

$$\begin{aligned} y_t &= \left(\sum_{i=1}^{4} \alpha_{0i} S_{it}\right) + \left(\sum_{i=1}^{4} \alpha_{2i} S_{it}\right) F_s(x_{st}, \gamma_s, \mu_s) \\ &\quad + \left(\sum_{i=1}^{p} \beta_{0i} y_{t-i}\right) + \left(\sum_{i=1}^{p} \beta_{2i} y_{t-i}\right) F_c(x_{ct}, \gamma_c, \mu_c) + \epsilon_t \end{aligned} \tag{4}$$

where $\alpha_{2i} = \alpha_{1i} - \alpha_{0i}$ and $\beta_{2i} = \beta_{1i} - \beta_{0i}$. Thus if α_{2i} is statistically significant, this shows significant changes in the coefficient of S_{it} across the regimes.

3.2 Extensions of the STAR Model

To allow for gradual institutional and technological changes, the above model needs to be extended by allowing for gradual changes in the above structure. Due to the lack of any better indicator, VST suggest that these changes can be captured by the time variable itself. This means that we have to estimate the following type of model:

$$\begin{aligned} y_t &= \left(\left(\sum_{i=1}^{4} \alpha_{00i} S_{it}\right) + \left(\sum_{i=1}^{4} \alpha_{02i} S_{it}\right) F_s(x_{st}, \gamma_s, \mu_s)\right) (1 - F_{st}(t, \gamma_{st}, \mu_{st})) \\ &\quad + \left(\left(\sum_{i=1}^{4} \alpha_{10i} S_{it}\right) + \left(\sum_{i=1}^{4} \alpha_{12i} S_{it}\right) F_s(x_{st}, \gamma_s, \mu_s)\right) F_{st}(t, \gamma_{st}, \mu_{st}) \\ &\quad + \left(\left(\sum_{i=1}^{p} \beta_{00i} y_{t-i}\right) + \left(\sum_{i=1}^{p} \beta_{02i} y_{t-i}\right) F_c(x_{ct}, \gamma_c, \mu_c)\right) (1 - F_{ct}(t, \gamma_{ct}, \mu_{ct})) \\ &\quad + \left(\left(\sum_{i=1}^{p} \beta_{10i} y_{t-i}\right) + \left(\sum_{i=1}^{p} \beta_{12i} y_{t-i}\right) F_c(x_{ct}, \gamma_c, \mu_c)\right) F_{ct}(t, \gamma_{ct}, \mu_{ct}) \\ &\quad + \epsilon_t \end{aligned} \tag{5}$$

Again, following the reasons behind the steps to equation (4) from equation (3), the above can be reorganised to get

$$\begin{aligned} y_t &= \left(\left(\sum_{i=1}^{4} \alpha_{00i} S_{it}\right) + \left(\sum_{i=1}^{4} \alpha_{02i} S_{it}\right) F_s(x_{st}, \gamma_s, \mu_s)\right) \\ &\quad + \left(\left(\sum_{i=1}^{4} \alpha_{20i} S_{it}\right) + \left(\sum_{i=1}^{4} \alpha_{22i} S_{it}\right) F_s(x_{st}, \gamma_s, \mu_s)\right) F_{st}(t, \gamma_{st}, \mu_{st}) \\ &\quad + \left(\left(\sum_{i=1}^{p} \beta_{00i} y_{t-i}\right) + \left(\sum_{i=1}^{p} \beta_{02i} y_{t-i}\right) F_c(x_{ct}, \gamma_c, \mu_c)\right) \end{aligned}$$

$$+ \left(\left(\sum_{i=1}^{p} \beta_{20i} y_{t-i} \right) + \left(\sum_{i=1}^{p} \beta_{22i} y_{t-i} \right) F_c(x_{ct}, \gamma_c, \mu_c) \right) F_{ct}(t, \gamma_{ct}, \mu_{ct})$$
$$+ \epsilon_t \qquad (6)$$

Thus α_{20i} and α_{22i} represent changes in the seasonal dynamics over time. Specifically, while α_{20i} represents how seasonals have changed in the period characterised by low values of the transition variable (called the 'base period' for brevity), α_{22i} shows how the regime-switching behaviour itself has changed over time. **This model is an extension of the TV-STAR model proposed by VST in that it allows for different type of regime-switching behaviour in the seasonal and cyclical components. In this sense, it encompasses both the TV-STAR model suggested by VST and the SEASTAR model suggested by Franses *et. al* (2000) and can be appropriately called the time-varying *seasonal* STAR (TV-*SEA*STAR) model[6].**

One important point needs clarification. It might be asked why we are allowing for regime-switching in the cyclical component when our focus is on seasonal fluctuations. There are two reasons for this. First, seasonality is stochastic in many cases (even if stationary) and this will be captured by the structure[7]. Not allowing for regime-switching in that will cause the regime-switching to be detected spuriously in the deterministic seasonal component. Secondly, there is empirical evidence for asymmetric behaviour of industrial production over phases of business cycles for several countries including India (see, for example, Sinha and Kumawat, 2005). Again, this would lead to bias in the results of nonlinearity in the seasonal component if we do not make allowance for regime-switching in the cyclical part.

One final observation on why we allow for different types of regime-switching in seasonal and cyclical components, i.e., why we need to extend the TV-STAR model. The reason is that the factors that explain a regime-switch in seasonals might be different from the corresponding factors for the cyclical component. Franses and van Dijk (2000) find empirical support for this. Using the same transition function (TF) for the two components in such cases would lead to biased results.

[6]To our knowledge this model has not been used by anyone so far.

[7]That's why we call the AR component the 'cyclical' component and not 'non-seasonal' component.

4 Methodology and Data

4.1 Methodology

In this paper we model the seasonal dynamics in the index of industrial production (IIP) for India. Due to the clear trend in this variable, which has been shown to be stochastic (Sinha and Kumawat, 2004 and Dua and Kumawat, 2005), we consider the first difference of log IIP. The procedure is as follows:

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

2. In the next step, we carry out a test for nonlinearity. This test cannot be done using the standard Wald test, since under the null hypothesis of no nonlinearity ($\gamma_s = 0$), the parameters μ_s and α_{2i} are not identified [8]. Therefore the test is carried out as per the procedure suggested by Terasvirta and Anderson (1992) and Terasvirta (1994), using the Taylor series approximation of the logistic function.

3. The SEASTAR models given in equation (4) are then estimated. Estimation is carried out in two steps. The initial values are first refined using the simplex method. This is followed by the application of the restricted BFGS method.

4. The models thus estimated are subjected to tests for serial correlation (first and fourth order). Again, these tests cannot be performed in a conventional manner, but are derived following the procedure suggested by Eitrheim and Terasvirta (1996).

5. The models thus obtained are extended to allow for time-variation, thus obtaining the TV-SEASTAR models.

One important aspect of the methodology is the selection of transition variables (x_{st} and x_{ct}, for instance). The discussion in Section 2 above suggests two types of economic indicators for regime-switching behaviour here. First, the level of industrial activity, which is measured by the fourth difference of log IIP[9] and its lags. The other indicator,

[8] The other way to test for no nonlinearity would be to test $\alpha_{2i} = 0 \; \forall i$. However, in that case γ_s and μ_s are not identified.

[9] It may be noted that our dependent variable is the first differenced log IIP, while as an indicator of business cycle, we take the fourth differenced log IIP. The latter is due to the fact that for India, quarterly data for other such variables, e.g. GDP, is not available for a long enough period. This should not affect our ersults since the objective is to model the seasonal behaviour of IIP. The annual growth rate of IIP merely serves as a proxy for overall economic activity.

as suggested by the discussion in Section 2, is an indicator of rainfall. For this we use the annual rate of growth of rainfall. In the following discussion, we denote the fourth difference of log IIP by $\triangle_4 y_t$ and the annual rate of growth of rainfall by R_t. Thus, we have two types of transition variables: lags of $\triangle_4 y_t$ and of R_t.

4.2 Data

The data for the index of industrial production is taken from the Reserve Bank of India database. We take quarterly data for the period 1981Q1 to 2006Q4. Data on rainfall is taken from the website *www.indiastat.com* and various issues of the Monthly Review of the Centre for Monitoring Indian Economy (CMIE).

5 Empirical Results

5.1 Graphical Analysis

We first examine the plot of seasonals in Figure 1. This presents the moving four-year average of the deviations of the seasonal means from the annual average. These are computed by running a 16-quarter rolling regression of the first differenced log IIP on the four seasonal dummies and taking the deviation of each coefficient from the average coefficient. The following points are clear from this plot:

- The first quarter growth is the highest, while the second quarter growth is the lowest. The latter has been below average throughout this period.
- The seasonals show a clear cyclical pattern, though this is more clear in the second and the third quarters.
- The first two quarters have been the most volatile, though of late, this volatility has declined substantially since early 1990s.
- The seasonal range, i.e., the difference between the highest and the lowest seasonals has also narrowed down substantially over time.

Our objective of our econometric exercise is to explain the variation in the seasonals. Specifically we test, whether (i) this variation in the seasonals can be explained by variablility of rainfall and that of the industrial production (ii) the gradual institutional changes in the economy, particularly those introduced in early 1990s have had a significant effect on the seasonals.

5.2 Econometric results

We select two models on the basis of the methodology discussed in the previous section. Results for these are presented in Tables 1 to 8 and are discussed in subsections 5.2.1 and 5.2.2 below. However, before the discussion of results, a few clarifications are required regarding notation. Instead of presenting the coefficients, we present the deviations from the average intercept for all the four seasons, along with the average intercept. Thus the coefficient for D_{it} represents the deviation of the i^{th} season from the average intercept, which is reported separately at the bottom. Low p-values for the coefficient for the i^{th} quarter imply that the IIP growth in this quarter is significantly different from the average growth[10].

5.2.1 TV-SEASTAR Model 1

The results for the TV-SEASTAR Model 1 are presented in Tables 1 to 4. In Table 1, four sets of coefficients are reported. The upper panel (with the heading 'Pre-transition') shows the coefficients in the component without $F_{st}(t, \gamma_{st}, \mu_{st})$, i.e., α_{00i} and α_{02i} respectively, $\forall i$; while the lower panel (with the heading 'Changes over time') shows how these change with time, i.e., α_{20i} and α_{22i} respectively, $\forall i$. For each of these panels, while the coefficient values under the set of columns entitled 'base regime' show the respective coefficients when both the variables have values low enough to give a value zero to the transition function, those in the other set show how these coefficients change between the regimes characterised by the transition variable (rainfall growth lagged once)[11]. The value of μ_{st} is 56 approximately, which means that transition occured around end-1994, i.e., shortly after introduction of market-oriented economic reforms in the Indian economy. The transition function given in Fig. 2 shows that the transition was not abrupt, it began in early 1993 and was complete by the end of 1995. Thus the pre-transition and post-transition periods given by this model coincide approximately with the pre-reforms and post-reforms periods respectively, for the Indian economy, showing that the seasonal dynamics changed with the structure of the economy.

Pre-transition period: In the top-left panel three coefficients are significant, of which the first quarter one is positive, while those for the next two quarters are negative.

[10]For instance, if in some period the first quarter coefficient is significant and positive but second quarter coefficient is insignificant, it means that in that period the quarterly growth rate of log IIP was significantly above annual average in the first quarter but equal to annual average in the second quarter.

[11]We report the results for the seasonal component only, since the focus of this paper is on seasonal dynamics and the cyclical component is included only to avoid the potential bias arising out of the cyclical component.

This means that in the pre-transition period the first quarter growth was the highest, while the second and the third quarters had smallest growth (significantly lower than the average), during the low rainfall periods. In the top-right panel only the first and third quarter coefficients are significant, of which the former is negative and the latter is positive. This means that the high growth of rainfall would cause the third quarter to gain at the cost of the first quarter. This result is seen more clearly in Table 2, which shows seasonals in the four regimes. In the top panel (which correspond to the pre-transition period), the coefficient of the third quarter is insignificant in the high-rainfall periods while it is negative in the low-rainfall periods.

As discussed earlier, the first quarter seasonal is the highest, and Dua and Kumawat (2005) have argued that this is powered by the kharif crop. The third quarter, on the other hand, is the period when the kharif crop is in the fields (as seen in Section 2, this crop is sown towards the end of the second quarter and harvested in the beginning of the fourth quarter), and hence significant purchases related to nurturing of this crop, such as fertiliser etc. are made during this period. When agricultural performance is good, the production in this quarter will go up. This explains the rise in growth rate in third quarter with growth of rainfall.

Changes between pre-transition and post-transition periods: The bottom panel in Table 1 describe the changes over time in this behaviour. In the left panel, only the first and the third quarters have significant coefficients. Of these, the former is negative while the latter is positive, implying that in the low-rainfall growth seasonal pattern, the first quarter growth rate has fallen[12](relatively, since we discuss deviation from average intercept), while the third quarter growth rate has risen. Again this is seen more clearly in Table 2. Here the left panel shows that (in the low-rainfall periods) in the pre-transition period, the third quarter growth was significantly below the average annual growth, but post-transition, it is not significantly different from the average annual growth.

It was seen above that the third quarter growth is caused by the needs of a growing crop. If the dependence of agriculture on rainfall has come down after reforms, then the third quarter seasonal (for the low rainfall periods) should go up in the post-transition period. This is exactly what the results here show.

[12]Since the dependent variable here is the quarterly growth rate of log IIP, the intercept for a particular quarter means the average rate of growth in that quarter, and here the coefficients represent the deviation of such rate of growth from average for all quarters.

One final result can be seen in the bottom-right panel of Table 1, which describes the changes in the response of seasonals to high growth of rainfall. In this panel the coefficients of the second and the third quarters are significant, of which the former is positive while the latter is negative. Two coefficients being significant means that the response of seasonals to growth of rainfall has changed over time. Table 3 presents response of the seasonals to growth of rainfall in the pre-transition and post-transition periods. The second set of columns in this table (under the heading 'Post-transition') shows that in the post-transition period, the high growth of rainfall pushes up the second quarter growth (compared to the average). The final result of this is seen in Table 2, which shows that while pre-transition, the high growth of rainfall would push up the third quarter growth rate at the cost of that for the first quarter (compare the two sets of results in the top panel) with the growth of rainfall, post-transition, (see the bottom panel) it pushes up the second quarter growth rate (again as measured as deviation from average annual growth rate). Since the second quarter has the lowest coefficient in high-rainfall periods in both the pre- and the post-reforms periods, this rise in the second quarter means narrowing down of seasonals post-transition. This is corroborated by the results in Table 4, the seasonal range in high-rainfall periods has fallen significantly over time. In other words, post-transition, the overall magnitude of seasonal variation has come down.

5.2.2 TV-SEASTAR Model 2

Results for TV-SEASTAR Model 2 are presented in Tables 5 to 8. The structure of Table 5 is similar to that of Table 1. The value of μ_{st} is 48, which corresponds to the last quarter of 1992. Again, this coincides with the introduction of reforms in the economy, implying that pre- and post-transition periods coincide with the pre- and post-reforms periods. The high value of γ_{st} means an abrupt regime-change at this point, seen clearly in Fig. 3. In the top-left panel of this table only two coefficients are significant, those for the first two quarters. Of these, the first one is positive, while the second one is negative, meaning that pre-transition the first quarter had the highest growth, while the second quarter had the lowest growth. In the top-right panel, which shows response of this pattern to economic activity, all the coefficients are insignificant, implying that pre-transition the seasonal pattern did not depend on the level of economic activity. In the bottom-left panel only the coefficients for the first and the third quarters are significant. Of these, the former is negative while the latter is positive, meaning that post-transition, the first quarter growth has fallen (in comparison to the annual average), while the third quarter growth has risen. As a result, in the post-transition period, the first quarter growth is not significantly different from the annual average, though the second quarter growth is still the lowest, and it is still significantly below the annual average (the coefficient for this quarter is negative and is significant). Since the first and second quarters were, respectively, the highest and the lowest growth quarters in the pre-transition period, the fall in the rate of growth in the first quarter (measured as deviations from average annual growth) means narrowing down of seasonals in the post-transition period as compared to the pre-transition period. Further, all the coefficients in the bottom-right panel of Table 5 are insignificant, implying that even the responsiveness of this behaviour to level of economic activity has not changed over time. This result can be seen more clearly in Table 7, which shows that the seasonal pattern does not depend on level of economic activity, neither pre-reforms nor post-reforms. Thus, the fall in magnitude of seasonal fluctuations, observed for low economic activity periods, holds for high economic activity periods also. Results in Table 8 corroborate this - the decline in the seasonal range is significant in both pre-transition and post-transition periods.

6 Conclusions

Our models are able to explain the important features of the seasonal dynamics in Indian industrial production. The results support the proposition that the seasonals in industrial production are affected by rainfall. The models capture both the change in the seasonal patterns as well as the narrowing down of the seasonals over time. The estimations show that the timing as well as the structure of these changes coincide with the changes in the character of the economy as it progressed towards a free-market economy in the post liberalization period. Over time, the dependence of agriculture on weather declined as the proportion of irrigated land rose, at the same time the share of agriculture in total GDP also declined. This result conforms with the findings of Dua and Banerji (2004a, 2004b) that show that before liberalization, the role of bad monsoons in triggering recessions was much more important. After liberalization, endogenous drivers of business cycles have gained prominence in sparking recessions and slowdowns in economic activity while the dominance of exogenous factors such as bad weather has diminished.

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Result Tables

Table 1: TV-SEASTAR Model 1

Component	Variable	Base regime		Regime change with R_{t-1}	
		Coef	$p-$val	Coef	$p-$val
Pre-transition	D_1	11.6011	0.0000	-6.1485	0.0047
	D_2	-5.9174	0.0016	-1.7450	0.3203
	D_3	-9.1965	0.0003	8.6691	0.0002
	D_4	3.5128	0.0752	-0.7755	0.6907
	Intercept	3.7418	0.0000	-1.6890	0.0747
Changes over time	D_1	-6.1023	0.0079	4.5073	0.0938
	D_2	-2.5958	0.2934	6.2056	0.0156
	D_3	11.5475	0.0000	-12.5920	0.000
	D_4	-2.8493	0.1931	1.8792	0.4152
	Intercept	-2.8270	0.0234	1.7736	0.1887
TF with R_{t-1}	γ_s [1]	–	–	–	75.6116
	μ_s	–	–	–	03.69
TF with t	γ_{st}	–	–	–	25.9654
	μ_{st}	–	–	–	55.8818 [2]

[1] For estimation the γ- parameters were normalised by sample standard deviation of the transition variable. For example, argument of the transition function for the seasonal component was $\left(-\frac{\gamma_s}{\sigma_s}(x_{st} - \mu_s)\right)$ and not $(-\gamma_s(x_{st} - \mu_s))$ as discussed in the section on methodology.

[2] Since the sample begins in 1981 first quarter, this corresponds to the last quarter of 1994.

Table 2: TV-SEASTAR Model 1: Seasonals in different regimes

Component	Variable	Base regime		Regime with high R_{t-1}	
		Coef	$p-$val	Coef	$p-$val
Pre-transition	D_1	11.6011	0.000	7.3383	0.0088
	D_2	-5.9174	0.0016	-7.6629	0.0001
	D_3	-9.1965	0.0003	-0.5277	0.7531
	D_4	3.5128	0.0752	2.7380	0.2340
	Intercept	3.7418	0.0000	2.0529	0.0045
Post-transition	D_1	5.4980	0.0006	3.8574	0.0023
	D_2	-8.5120	0.0000	-4.0529	0.0001
	D_3	2.3504	0.1839	-1.5720	0.1742
	D_4	0.6636	0.722	1.7675	0.1318
	Intercept	0.9132	0.7222	0.9995	0.1911

Table 3: TV SEASTAR Model 1: Changes in Seasonals

Variable	Pre-transition		Post-transition		Difference	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
D_1	-6.1485	0.0047	6.4058	0.2957	4.5073	0.0938
D_2	-1.7450	0.3203	4.4590	0.0159	6.2056	0.0156
D_3	8.6691	0.0002	-3.9223	0.0183	-12.5920	0.0000
D_4	-0.7550	0.6907	1.1039	0.5029	1.8792	0.4152
Intercept	-1.6890	0.0747	0.0842	0.9346	1.7736	0.1887

Table 4: TV-SEASTAR Model 1: Seasonal range in different regimes

Phase	Base regime		Regime with high R_{t-1}	
	Coef	$p-$val	Coef	$p-$val
Pre-transition	17.5186	0.0000	13.1154	0.0000
Post-transition	14.0010	0.0000	7.9103	0.0008
Change	-3.4668	0.2062	-5.1900	0.0020

Table 5: TV-SEASTAR Model 2

Component	Variable	Base period		Regime change with $\triangle_4 y_{t-2}$	
		Coef	$p-$val	Coef	$p-$val
Pre-transition	D_1	6.0684	0.0002	2.0985	0.1390
	D_2	-5.9952	0.0009	0.4856	0.6876
	D_3	-2.1185	0.2192	-1.2801	0.2773
	D_4	2.0433	0.2658	-0.3039	0.3011
	Intercept	1.7198	0.0148	3.5223	0.0002
Changes over time	D_1	-5.3316	0.0010	-1.3509	0.4374
	D_2	2.2050	0.1809	-0.9824	0.5271
	D_3	4.3396	0.0113	0.8730	0.5710
	D_4	-1.2130	0.5632	1.4603	0.3449
	Intercept	-0.6249	0.4951	-3.2782	0.0054
TF with $\triangle_4 y_{t-2}$	γ_s	–	–	–	77.5941
	μ_s	–	–	–	5.8122
TF with t	γ_{st}	–	–	–	1050.7006
	μ_{st}	–	–	–	48.00[1]

[1] This corresponds to the last quarter of 1992.

Table 6: TV-SEASTAR Model 2: Seasonals in different regimes

Component	Variable	Base period		Regime with high $\triangle_4 y_{t-2}$	
		Coef	$p-$val	Coef	$p-$val
Pre-transition	D_1	6.0684	0.0002	8.1669	0.0000
	D_2	-5.9952	0.0009	-5.5096	0.0001
	D_3	-2.1185	0.2192	-3.3966	0.0381
	D_4	2.0433	0.2658	1.7394	0.6577
	Intercept	1.7198	0.0148	5.2421	0.0000
Post-transition	D_1	0.7368	0.5826	1.4844	0.2987
	D_2	-3.7902	00055	-4.2870	0.0060
	D_3	2.2231	0.1126	1.8160	0.2218
	D_4	0.8303	0.5345	0.9866	0.4809
	Intercept	1.0949	0.0986	1.3390	0.2002

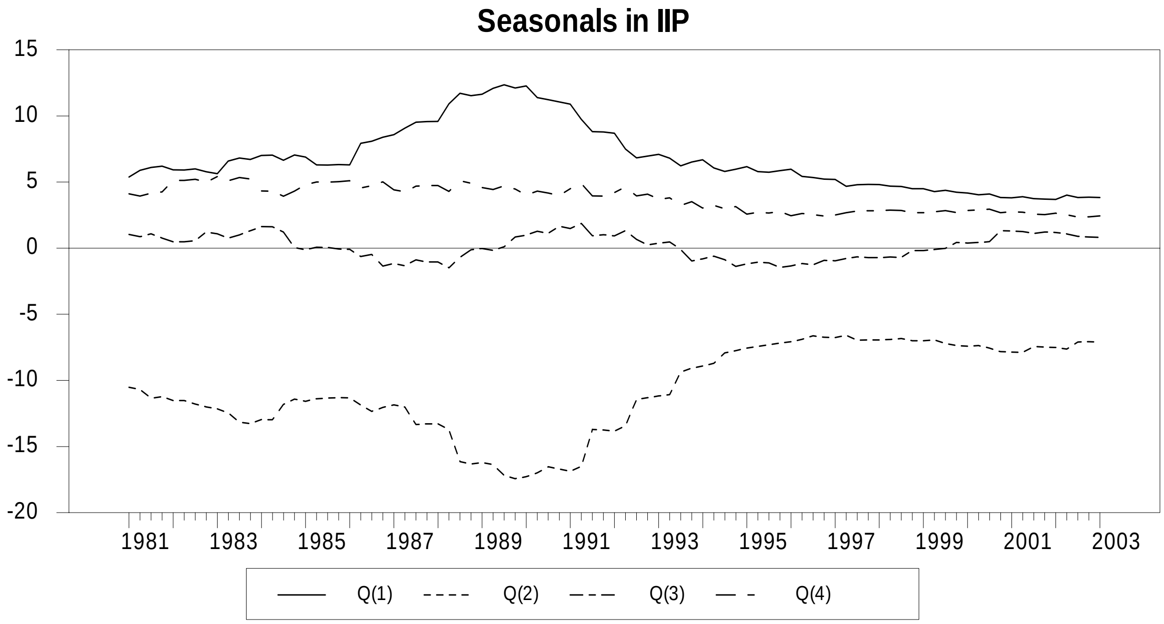
Table 7: TV SEASTAR Model 2: Changes in Seasonals

Variable	Pre-transition		Post-transition		Difference	
	Coef	$p-$val	Coef	$p-$val	Coef	$p-$val
D_1	2.0985	0.1390	0.7476	0.4801	-1.3509	0.4374
D_2	0.4856	0.6876	-0.4968	0.6226	-0.9824	0.5271
D_3	-1.2801	0.2773	-0.4071	0.6830	0.8730	0.5710
D_4	-1.3039	0.3011	0.1564	0.8654	1.4603	0.3449
Intercept	3.5223	0.0002	0.2441	0.7361	-3.2782	0.0054

Table 8: TV-SEASTAR Model 2: Seasonal range in different regimes

Phase	Base regime		Regime with high R_{t-1}	
	Coef	$p-$val	Coef	$p-$val
Pre-transition	12.0636	0.0000	13.6765	0.0000
Post-transition	4.5271	0.0365	5.7714	0.0167
Change	-7.5366	0.0026	-7.9051	0.0049

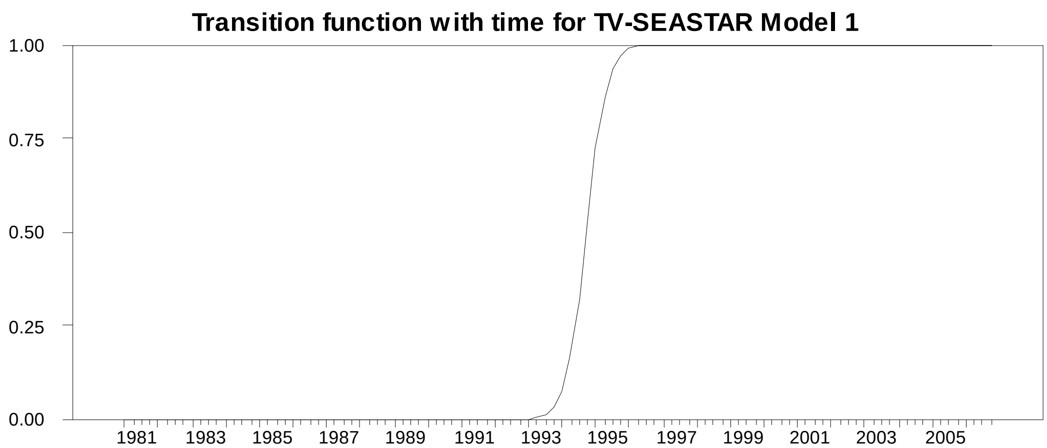
Fig. 1



Notes:

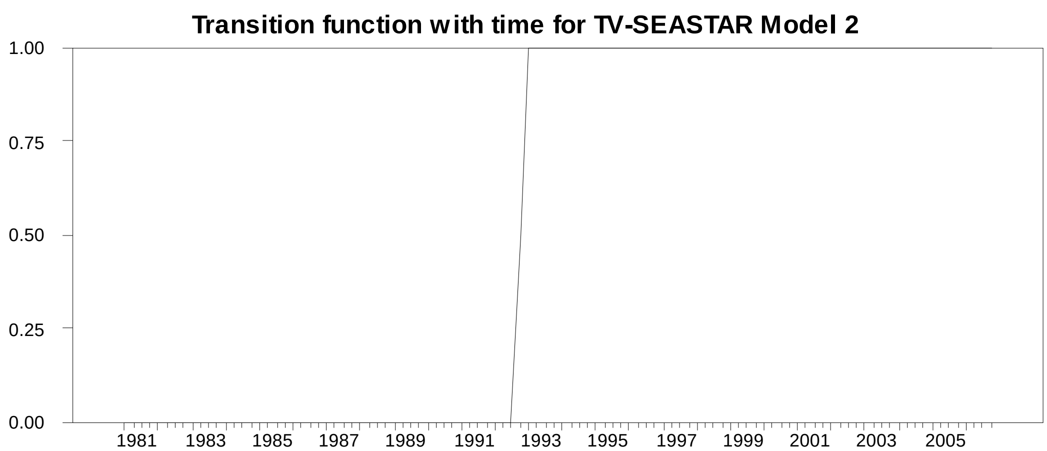
1. The value for a given quarter represents deviation of sample mean of first differenced log IIP in that quarter from average of such sample means for all quarters during that period, thus giving the quarterly growth rate of IIP relative to the average quarterly growth rate over the year.
2. These were calculated by running the rolling regression of first differenced log IIP on four seasonal dummies and then taking deviation of each quarter from the average of the four coefficients. The window size was 16 (implying that each coefficient gives average growth rate of first differenced log IIP in that period for **four** 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 1991q1-1994q4.

Fig. 2



Transition function with time for TV-SEASTAR Model 1
1.00
0.75
0.50
0.25
0.00
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005

Fig. 3



Transition function with time for TV-SEASTAR Model 2
1.00
0.75
0.50
0.25
0.00
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005