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Disaggregated Indian Industrial Cycles: A spectral analysis

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Abstract

We study the structure and dating of disaggregated Indian industrial cycles and spectral causality from different policy parameters to these cycles. The scattered pattern of peaks and troughs after 2013, suggests some industries continued to do well during an extended slowdown. Post 2011 industrial cycles have been shallow and short. The exchange rate, currency, credit, nominal and real interest rates all affect industry cycles, but differences in impact by industry type may be due to the structure of the economy. Cash and credit are more important for consumer non-durables, while interest rates affect consumer durables and capital goods. Interest rates do matter but in combination with currency and credit. Co-movement across disaggregated industry points to some common drivers. Stabilization policies need to be used more and fine-tuned based on research. Results on the dating and duration of industry cycles, their cyclicality, phase shifts, amplitude, lead-lag sectors, duration asymmetry and co-movement can help design appropriate policies.

Keywords: Industrial cycles, co-movement, coherence, lead/lag, business cycle dating, spectral causality, macroeconomic stabilization.

JEL Code: E23, E32, C32.

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1. Introduction

Since the implementation of economic reforms of the 1990s, India, an emerging market economy, has experienced fast-paced growth; its real gross domestic product (GDP) has increased more than 300% from 1990 to 2017, with an average annual growth rate of about 6%. However, the scenario of industrial production was more complicated – the quarterly data of the index of industrial productivity (IIP) showed an average of about 7% growth till 2010, while it plummeted to an average of about 3% from 2011 to 2019. Since 2011, India faced a prolonged industrial slowdown.

Although there has been a great deal of empirical work on Indian business cycles (Pandey et. al., 2019, 2017; Dua and Banerji, 2012; Nandi, 2011), most studies have focused on the correlations between business cycles and aggregate IIP series, as far as industrial productivity is concerned. In contrast, little is known about the structure and dating of productivity cycles of disaggregated industries, and the idiosyncratic effect of policy parameters on different group of industries. The concentration of cyclical phases is a cornerstone of the classical definition of cyclical co-movement (as suggested by Burns and Mitchell, 1946), but very little is known about the co-movement of phase shifts across Indian industries – which carries important information regarding developments of economic activity across industries. A better understanding of the phase shifts in India's disaggregated industrial production cycles is particularly useful for policymakers and government officials, not only in devising target policies to attenuate the economic effect of cyclical fluctuations, but also for promoting growth in targeted industries.

A handful of studies have investigated the phase shifts in business cycles like Harding and Pagan, 2006, Chauvet and Piger, 2008, Stock and Watson, 2014, Iacoviello, 2015, Mian et. al., 2017, and Bloom et. al., 2018. Despite being one of the largest and one of the most significant emerging countries in the world, however, the phase shifts in India's industries have not been studied[1]. Considering the asymmetry of phase shifts, a growing body of literature has explored causality in frequency domain, which unearths causality between two or more variables across different frequencies, including studies by Assenmacher-Wesche and Gerlach (2007, 2008a, b); Gronwald (2009); Tiwari (2012a, b); and Wei (2014). However, to the best of our knowledge, none of the studies have analysed the causality of policy parameters on industrial production cycles.

The analysis of the empirical pattern of cyclical industrial dynamics, or industrial cycles as they are commonly known, forms the basis of modern business cycle models (Chang and Hwang, 2015). The industrial cycles continue to behave in ways described by Schumpeter in his seminal work (1912, 1934), with the troughs (upturns) creating an opportunity for profit and peaks (downturns)

[1] On 2017, India's share of world GDP was around 3%, making it the fifth highest in the world.

creating an opportunity for restructuring (Tan and Mathews 2009). These dynamics have caused the issue of cycles to enter key debates, primarily concerning the timing of innovation and investment. In another strand, it has also been argued in the literature (starting from Mankiw and Reis, 2003), that in an inflation-targeting regime, the weight of a sector in the stability price index depends on the sector's characteristics like cyclical patterns, co-movement and, phase shifts. Following the undertaking of inflation targeting by the Reserve Bank of India (India's central bank), our results can be used for such analysis.

In this paper, we take a step toward filling the above gaps. More specifically, we provide empirical evidence on – (1) the structure and dating of disaggregated Indian industrial cycles and (2) spectral causality from different policy parameters to these cycles. Using a panel of IIP use-based data, we find that the average duration of cycles is longer during expansions than during recessions, and this asymmetry is highest for basic industries. Consumer durables show most frequent phase shifts, while for the aggregate industry, it is very low. Amplitude is highest for capital goods industries, much above the aggregate. High amplitude is found with low duration asymmetry. It is also observed that the co-movement across phase shifts is high and is more significant during troughs so that a broad-based upturn is possible with the correct policies. Phase shifts tend to coincide across industries, but the concentration is higher during recessions compared to expansions. There is more persistence of the same industry in consecutive peaks than in troughs. Bi-directional causality exists between industry types and monetary policy variables. The exchange rate, currency, credit, nominal and real interest rates all affect industry cycles, but differences in impact by industry type may be due to the structure of the economy. Cash and credit are more critical for consumer non-durables, while interest rates matter for consumer durables and capital goods. Basic goods are somewhat insulated, except for working capital, perhaps because of more government ownership. Real interest rates weakly affect basic goods and intermediates.

From Figure 1, we observe cycles for different sectors (based on usage) are quite distinctive. For robustness, we have used two types of filters to extract cycles from the deseasonalized[2] data – the Hodrick Prescott (HP) filter (1997) and the bandpass filter proposed by Christiano and Fitzgerald (CF) (2003). It has been observed that although for annual series, there is a deviation of HP filter from band-pass filters like CF and Baxter-King (BK)[3] (1999), for quarterly series these filters yield similar cycles. Although HP filter does not amplify high-frequency noise, it allows much of the high-frequency noise to be left outside the business cycle frequency band. This has been complemented by the low pass band-pass filter (in our case, CF filter) which has the downside of underestimating the

[2] We have used Census X-13 ARIMA-SEATS seasonal adjustment program to filter out the seasonal components.
[3] Due to shorter data time span, BK filter will not be appropriate as it leads to data loss in the terminal quarters.

cyclical component. We follow Rand and Tarp (2002)[4] and employ both HP filter and CF filter to extract cycles.

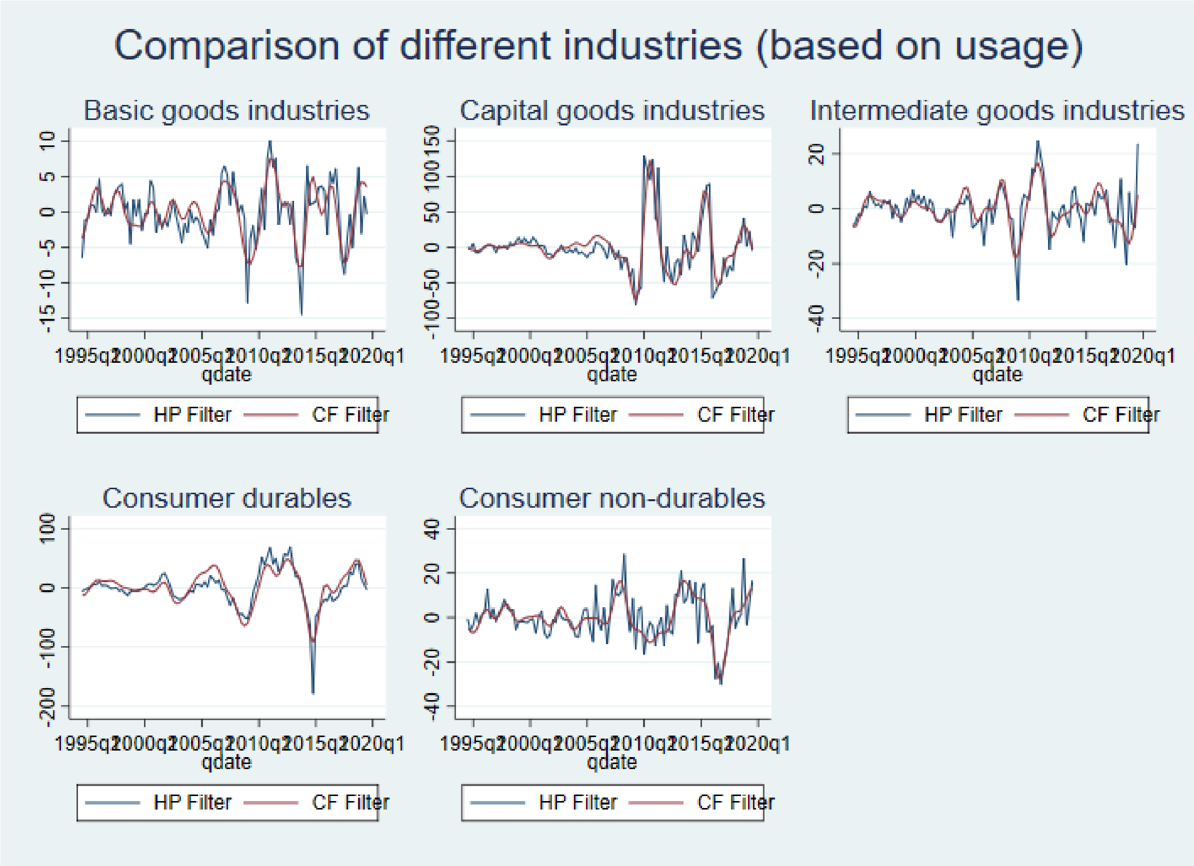

Figure 1: Industrial cycles (Hodrick Prescott Filter and Christiano Fitzgerald filter)

We believe our paper contributes to two strands of literature – the Indian business cycle literature (Pandey et al. 2017; Dua and Banerji 2012) and the macroeconomic study of industries (Chang and Hwang 2015; Foerster, Sarte and Watson 2011; Tan and Mathews 2009). Business cycles are somewhat neglected in India (along with other emerging economies[5]) with an emphasis on structural reform. Being the first study of industrial cycles of India, our paper will give an additional dimension to the literature, by unearthing the patterns and synchronicity of sectoral cycles and will motivate business cycles theories to incorporate the sectoral patterns for India. It will also serve policymakers by informing them about the patterns of a specific sector concerning a change in parameters and enable more informed stabilization policies. Our paper will give critical insights on the patterns of sectoral cycles for analysts interested in predictions for a newly liberalized, globalised and privatized developing economy, where market forces are slowly coming into play.

[4] Rand and Tarp (2002) have used HP filter and BK filter.
[5] We could only find only one other study, on China, by Kong et. al. (2019).

The rest of the paper has been arranged as follows: Section 2 outlines the theoretical underpinnings. Section 3 explains the data and variables. Results of our study have been placed in section 4, while section 5 concludes our study.

2. Methodology

2.1 Industrial cycles dating

We identified turning points of individual industrial cycles by applying the algorithm proposed by Harding and Pagan (2002) to the IIP series cycles (generated by HP filter). We use this algorithm since it does not depend on any particular definition of trend components from the raw series, which in turn avoids potential problems inherent in de-trending methods. Due to the extensive usage of this algorithm in the literature, it is comparable with other studies.

Implementation of Harding and Pagan (2002) (a quarterly variant of the Bry and Boschan (1971) algorithm) involves the following stages:

1. A peak is defined in a time series $\{y_t\}_{t=1}^{T}$ as occurring at time t if $y_t = \max\{y_{t-2}, y_{t-1}, y_t, y_{t+1}, y_{t+2}\}$ and a trough is defined as occurring at time t if $y_t = \min\{y_{t-2}, y_{t-1}, y_t, y_{t+1}, y_{t+2}\}$.
2. Check whether these peaks and troughs satisfy predetermined 'censoring rules' as described below.

Censoring rules: (i) peaks and troughs occur alternately, and that (ii) a phase and a complete cycle have minimum durations. If these requirements are not fulfilled, the least pronounced among adjacent turning points is eliminated. In this paper, we set the minimum duration of a phase to be 2 quarters and that of a cycle to be 5 quarters.

After finding out the peaks and troughs of the industrial cycles[6], we have computed various summary statistics to give an idea of the cyclical characteristics of the industries, namely, cyclical durations, duration of asymmetry, number of recession and expansion cycles and amplitude – across both the phases (expansionary phase and recessionary phase). Duration asymmetry is defined as how long/short the expansionary cycles with respect to recessionary cycles and is measured by the ratio of the average duration of expansion to that of recession. The amplitude of the expansion and the recession phases of the business cycles is a measure of the extent that economic activity changes during the phase.

[6] Here, we have used the IIP use-based series for tractability.

2.2 Co-movement indices

Following Harding and Pagan (2002), Artis et. al. (2004) and Chang and Hwang (2015), the degree of concentration of co-movement between two industrial cycles can be measured using concordance and diffusion indices.

The concordance index measures the proportion of time the two cycles are in the same phase, and it is used in two different ways – pairwise concordance indices between industries and concordance of individual industries with the aggregate IIP. The concordance index is measured by,

$$Concordance_{i,j} = \frac{1}{T}\sum_{t=1}^{T}[C_{it}C_{jt} + (1 - C_{it})(1 - C_{jt})]$$

where C_{it} and C_{jt} are binary variables indicating contractions of industries i and j respectively[7]. Here, j can be other industries or aggregate IIP.

Another measure of comovement, the diffusion index measures the proportion of industries sharing the same phase at a point in time. Diffusion index for contraction is measured by,

$$Diffusion_t = \sum_{i=1}^{N} w_{it}C_{it}\ ,\sum_{i=1}^{N} w_{it} = 1\ \forall\ t = 1, \dots, T$$

where w_{it} is the weights for each industry and in this paper, we have used equal weights for all the industries.

2.3 Distribution of turning points

To determine the leading, lagging and coincident industries, with respect to the aggregate IIP series, we employ the dynamic correlation (using autocovariance function) and note down the lags in which the two series have the highest correlation.

In this section, we also calculate transition probabilities (τ_{ij}) for IIP peak to peak transition and trough to trough transition separately. It measures the average probability of industries moving into j^{th} group (leading, lagging, coincident or acyclical) among the industries that were present in the i^{th} group between two adjacent aggregate IIP peaks and between two adjacent aggregate IIP troughs.

Last, we calculate the concentration of turning points asymmetry, to find whether the distributions of IIP sectoral turning points have the same concentration between aggregate IIP peaks and troughs. We define a turning point cluster whose distance from the given aggregate IIP turning

[7] $C_{it} = 1$ if industry i is in a contractionary phase and $C_{it} = 0$, otherwise.

point is less than 8 quarters (Harding and Pagan 2006). Let Λ_{ij}^{P} be the j^{th} peak of industry i and m_k be the k^{th} peak in the aggregate IIP cycle. Then, the k^{th} peak cluster centered around m_k is,

$$\sigma_k = \{\Lambda_{ij}^{P} \mid d(m_k - \Lambda_{ij}^{P}) < d(m_l - \Lambda_{ij}^{P})\ \forall\ l \neq k\ and\ d(m_k - \Lambda_{ij}^{P}) \leq 8\}$$

2.4 Causality (frequency domain)

Here we employ the notion of causality as introduced by the seminal work of Granger (1969, 1980). The basic idea being, a variable, say X_t is said to cause another variable, say Y_t, if X_t contains information about future Y_t that is not contained in the information set, consisting of past Y_t. The methodology proposed by Granger (1969) has been used in numerous studies spreading across different fields. The conventional causality tests are conducted as Wald tests in Vector Autoregression (VAR) models, which produce a single, one-shot statistic regarding predictability while implicitly ignoring the possibility of causal dynamics across different frequencies (Ciner 2011a). Granger and Lin (1995) showed that the extent and the direction of causality could differ between frequency bands. It will be useful for us to provide short-term spillovers versus long-term causal relations between the policy parameters and the industries, which can be accomplished by examining the test statistic across the full spectra.

Causality in the frequency domain have been proposed by Geweke (1982) and Hosoya (1991); however, due to nonlinearities, the test statistics in the frequency domain has been found difficult to estimate. By building on the earlier works of Geweke (1982), Breitung and Candelon (2006) have shown test statistics can be calculated by imposing linear restrictions on the autoregressive (AR) parameters in the VAR model. They have also found that their methodology has good size properties in Monte Carlo experiments and Lemmens et al. (2008) concluded that the approach was the most efficient among the ones considered.

Geweke (1982) considers two-dimensional vector, say X_t and Y_t with a finite order VAR (p):

$$\theta(L)\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} \theta_{11}(L) & \theta_{12}(L) \\ \theta_{21}(L) & \theta_{22}(L) \end{bmatrix}\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \epsilon_t$$

where $\theta(L) = I - \theta_l L - \cdots - \theta_p L_p$ is a 2×2 lag polynomial and $\theta_l, \dots, \theta_p$ are 2×2 autoregressive parameter matrices, with $L^k X_t = X_{t-k}$ and $L^k Y_t = Y_{t-k}$. The error vector ϵ_t is white noise with zero mean and $E(\epsilon_t, \epsilon_t') = \Sigma$, where Σ is positive definite. The MA representation of the system is given by,

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix}\begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}$$

with $\Psi(L) = \theta(L)^{-1}G^{-1}$ and G is the lower triangular matrix of the Cholesky decomposition.

$G'G = \Sigma^{-1}$, such that $E(\eta_t \eta_t') = I$ and $\eta_t = G\epsilon_t$. The causality test developed by Geweke (1982) which measures linear feedback from X_t to Y_t at frequency, ω can thus be written as:

$$M_{X\Rightarrow Y}(\omega) = \log\left[1 + \frac{\left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right]$$

when $\left|\Psi_{12}\left(e^{-i\omega}\right)\right| = 0$, X_t does not Granger cause Y_t at frequency ω. Breitung and Candelon (2006) have showed that this condition leads to

$$\left|\theta_{12}(e^{-i\omega})\right| = \left|\sum_{k=1}^{p} \theta_{k,12}\cos(k\omega) - i\sum_{k=1}^{p} \theta_{k,12}\sin(k\omega)\right| = 0$$

with $\theta_{k,12}$ being the (1,2) element of θ_k, such that a sufficient set of conditions for no causality is given by,

$$\sum_{k=1}^{p} \theta_{k,12}\cos(k\omega) = 0$$

$$\sum_{k=1}^{p} \theta_{k,12}\sin(k\omega) = 0$$

The null hypothesis of no causality for frequency ω is tested using a standard F-test for the linear restrictions on the coefficient of the first equation of the VAR model. The F-test follows an $F(2, T - 2p)$ distribution for every ω between 0 and π, with T being the length of the time series.

This test proposed by Breitung and Candelon (2006) is straightforward to implement and has good power and size properties. Several researchers applied this methodology to study frequency domain causality (Assenmacher-Wesche et al. 2007, 2008a, b; Bodart and Candelon 2009; Gronwald 2009; Ciner 2011a, b; Fromentin and Tadjeddine 2020).

3. Data

In this paper, we have used IIP use-based data from 1994Q4 to 2019Q3 and IIP sectoral data from 2004Q2 to 2019Q3[8], from the Ministry of Statistics and Programme Implementation (MOSPI), India. The IIP sectoral data for India is available for 2-digit industries, and the IIP use-based data is classified in 5 broad categories – basic industries, capital goods industries, intermediate goods industries, consumer durables and consumer non-durables. For the first part of our paper concerning the cyclical pattern of industrial cycles, disaggregated data is necessary, and thus, we have used the most disaggregated data available for India, IIP 2-digit sectoral data. For tractability, IIP use-based

[8] This is done due to data limitation of sectoral IIP.

data has been used in the next part of our paper concerning the relation of industrial cycles with policy parameters. Although the same can be done using IIP sectoral data, we keep it as an area for future study.

The IIP sectoral data follows NIC 2004 classification code for the base year 2004-05 and NIC 2008 classification code for the base year 2011-12. Concordance has been done for the industries to NIC 2004 classification, and wherever necessary, we have taken a weighted average of two (or more) industries to concord[9]. Policy variables, namely, exchange rate (INR/USD), M0, M1, M3, 91 days government securities (primary), 10 years Govt. securities yield, consumer price index, wholesale price index have been taken from the Reserve Bank of India's Database of Indian Economy (DBIE).

All the variables have been deseasonalized using Census X-13 ARIMA-SEATS seasonal adjustment program. All the variables are stationary at the first difference.

We have constructed realized real interest rate (RRIR) as follows:

$$RRIR\ (Non-consumer\ industries) = (G-secs\ 10\ years\ yield)_{-1} - WPI\ (manufacturing)\ inflation$$

$$RRIR\ (Consumer\ industries) = (G-secs\ 10\ years\ yield)_{-1} - CPI\ inflation$$

While reserve money M0 proxies currency whose use dominates parts of the Indian economy, M1 proxies demand deposits used for working capital, M3 is close to aggregate credit, and the 91 days government securities is the risk-free short-run nominal interest rate. Two RRIRs are obtained. First, we subtract next period wholesale price inflation from the long-run government securities rate. Second, we subtract CPI inflation from it. The relevant product real interest rate for an industry requires subtracting inflation in the product it produces from the nominal rate. In the absence of such detailed price data, we use CPI for consumer goods industries and WPI, which is closest to producer prices, for the others.

We classify the 2-digit industries into their respective usage-based categories using the maximum weight method (Table 1A, appendix). NIC 17 (Textiles), NIC 20 (Wood & Products of Wood & Cork except Furniture, Articles of Straw & Plating Materials), NIC 21 (Paper & Paper Products), NIC 25 (Rubber & Plastic Products) and, NIC 28 (Fabricated Metal Products except Machinery & Equipment) is classified into intermediates. Basic goods consist of NIC 23 (Coke, Refined Petroleum Products & Nuclear Fuel), NIC 26 (Other Non-Metallic Mineral Products) and NIC 27 (Basic Metals). NIC 29 (Machinery and Equipment nec), NIC 34 (Motor Vehicles, Trailers, Semi-trailers), NIC 30 (Computer, electronic and optical products) and NIC 31 (Electrical Machinery & Apparatus nec) is classified as capital goods industries. NIC 36 (Furniture Manufacturing nec) and

[9] We have not taken the previous IIP series (base year 1994-95) because it follows NIC 1987 and the concordance lead to a significant aggregation of different industries.

NIC 35 (Other Transport Equipment) consists of consumer (C) durables. NIC 15 (Food Products & Beverages), NIC 16 (Tobacco Products), NIC 18 (Wearing Apparel, Dressing and Dyeing of Fur), NIC 19 (Luggage, Handbags, Saddlery, Harness & Footwear, Tanning & Dressing of Leather Products), NIC 22 (Publishing, Printing & Reproduction of Recorded Media) and, NIC 24 (Chemicals & Chemical Products) is classified into consumer (C) nondurables. Electricity and mining are considered as Basic goods.

4. Result

Using deseasonalized data, we checked stationarity and normality of the cycles and did suitable modifications[10] wherever required. The cyclical component was extracted using the HP filter and the CF filter. We find that the aggregate IIP shows a 4-year cycle duration irrespective of the filter chosen (Table 2A, appendix). The average duration of a HP filtered cycle in the individual series is around 5 years whereas the maximum duration has been observed in "Mining" and "Rubber & Plastic products" industries (7.5 years). It has also been observed that "C durables" exhibit the highest average duration (7.5 years) whereas "C non-durables" exhibit the shortest duration (4.67 years). Our result is robust even when we consider CF filtered cycles. In the literature, it has been observed that a typical business cycle in India has a duration of 5 years whereas we find that the industrial cycles have very diverse durations, ranging from 3 years to 7.5 years. Capital goods and C durables tend to have longer cycles.

We have also carried out cyclicality tests of sectoral industrial cycles with respect to aggregate IIP series. Table 3A (appendix) shows the correlation coefficient along with 10% significance level. We find that only "Tobacco products" industry is countercyclical with the aggregate IIP series. Highest procyclicality is observed in "Machinery and Equipment nec" and the result is same if we consider CF filtered cycles. Most industries are pro-cyclical, while a few, largely C non-durables are acyclical, only one is countercyclical.

The dynamic correlation along with the lags (leads) has been given in Table 4A (appendix), both for HP filtered and CF filtered cycles. For example, "Other Non-Metallic Mineral Products" is a coincident industry with the aggregate IIP series because we observe the highest correlation at lag = 0. Here we observe that there is a high variation of leading/lagging industry even within the usage group, but there is a higher concentration of lead and coincident industries among basic and capital goods.

4.1 Industrial Cycles Dating

Since India, following the liberalization episodes of the 1990s has not had any actual fall in output levels. Hence, the classical approach is not appropriate for the identification of cyclical turning

[10] All the series were stationary at the first difference.

points (Pandey et al. 2017). Boschan and Banerji (1990) pointed out that growth-cycle approach is more appropriate when the identification of business cycle dates is desired. So, here we have applied the dating algorithm on the cycles generated by the HP filter[11] on the levels of the IIP series.

$$IIP\ level\ form \xrightarrow{Hodrick-Prescott\ Filter} IIP\ cycles \xrightarrow{Harding-Pagan\ Algorithm} Turning\ points$$

Table 1 reports the summary statistics for cyclical durations (peak to peak for recessions and trough to trough for expansions) based on usage of the sectors. We find that the average cyclical duration of the aggregate IIP series is 7 quarters during expansion and 5 quarters during recession. We also observe that the average duration of cycles during expansion takes longer than during recessions, except C goods. It can also be observed from the duration asymmetry (Table 2), which is basically the ratio of cyclical duration during expansion to that during recession. We find that the industries show varying duration asymmetry with "Intermediate" and "Capital" industry groups showing the higher duration asymmetry than aggregate IIP. For "Intermediate" an expansion in this group can take about 1.49 times more than during recessions. The "C durables", on an average, exhibit the lowest duration asymmetry.

Cycle Durations	Mean		Maximum		Minimum		SD	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
Basic	5	5.45	10	12	2	2	2.36	2.94
Capital	6.89	4.87	15	10	2	2	3.84	2.92
Intermediate	6.29	4.55	12	9	2	2	2.87	2.37
C durables	5.1	6.63	12	10	2	2	3.45	3.38
C non-durables	6.46	6.86	15	16	2	3	3.43	3.76
Aggregate	7	5	12	9	2	2	4	2.94

Table 1: Duration of cycles (aggregate usage level) (in years)

Duration Asymmetry	Mean	Maximum	Minimum	SD
Basic	0.96	1.27	0.64	0.26
Capital	1.43	1.71	1.24	0.20
Intermediate	1.49	2.6	0.92	0.65
C durables	0.79	1.02	0.56	0.32
C non-durables	0.97	1.29	0.75	0.26
Aggregate	1.4			

Table 2: Duration Asymmetry (aggregate usage level)

Now, we shift our focus to the number of cycles observed by the industries during our period of study (Table 3 and 4). We observe that "Durables" and "Basic" shows more frequent phase shift

[11] We have also applied the same technique on CF cycle, and it will be made available on request. It shows the robustness of our findings.

both during recessions (Table 6) and whereas during expansions (Table 7) most phase shift happens in "Basic". "Non-durables" exhibit the lowest number of phase shifts both during expansions and recessions.

Recession Cycles	Mean	Maximum	Minimum	SD
Basic	5	7	3	1.58
Capital	4.75	6	4	0.96
Intermediate	4.8	6	4	0.84
Durables	5	6	4	1.41
Non-durables	4	5	3	0.63
Aggregate	5			

Table 3: Recession cycles (Peak to Peak)

Expansion Cycles	Mean	Maximum	Minimum	SD
Basic	4.4	6	3	1.34
Capital	3.75	5	3	0.96
Intermediate	4	5	3	0.7
C durables	4	5	3	1.41
C non-durables	3.67	4	3	0.52
Aggregate	4			

Table 4: Expansion cycles (Trough to Trough)

Next, we turn our focus to amplitude of the cycles. Amplitude during expansion and recession phases of a cycle measures the extent of economic activity change during the phase. It is observed from Table 5, that the average amplitude of "Capital" goods industries is much higher than other industries as well as the aggregate IIP series. This is observed both in expansionary and recessionary phases. The lowest average amplitude is observed in "Basic" industries during both expansionary phase and recessionary phase. Industries such as capital goods and consumer goods that have the most amplitude tend to have the least asymmetry.

Amplitude	Mean		Maximum		Minimum		SD	
	Expansion	Recession	Expansion	Recession	Expansion	Recession	Expansion	Recession
Basic	10.18	10.14	25.6	23.2	2.7	2.3	6.67	6.71
Capital	104.65	104.98	341.9	321.5	21	6	101.52	115.43
Intermediate	14.35	14.54	45.6	31.9	3.6	4.4	9.3	8.19
C durables	40.17	20.24	72	54.5	11.5	31.7	22.57	8.57
C non-durables	20.47	22.85	85.4	75.9	5.1	3.1	18.42	17.56
Aggregate	10.64	10.03	17.9	19	2.6	1.8	6.64	7.21

Table 5: Amplitude of cycles (aggregate usage level)

4.2 Co-movement and phase-shifts

4.2.1 Concordance and diffusion index

Despite the differences in the duration properties, using the disaggregated individual industries cycle, we find that phase shifts tend to coincide across industries. To quantify the degree of concentration of cyclical phases, we adopt two measures of co-movement, diffusion and concordance indices, in the spirit of Chang and Hwang (2015).

From Table 6, we find a high degree of concordance across industries ranging from 0.66 to 0.49, with a mean of 0.59, suggesting that a randomly chosen pair of industries are in the same cyclical phase about 59% of the time. The concordance index with the aggregate IIP series also averages 0.65.

	Mean	**Maximum**	**Minimum**
Pairwise	0.59	0.66	0.49
Aggregate	0.65		

Table 6: Concordance Index

Table 7 reports the summary of the diffusion index and Figure 2 displays the diffusion index over time. In the Figure, shaded bars represent recessionary phases in aggregate IIP growth cycles. Table 8 lists turning points for the same[12]. We report the diffusion index in the contractionary phase. This index measures how widely contractions are spread in the industries. It is observed the fraction of industries experiencing a recession rises sharply during every IIP recession, whereas it remains very low during IIP expansions. During aggregate IIP recessions, the average fraction of industries in recession is 45% whereas, during IIP expansions, the fraction is only 28%.

Taking both indices together, confirms the co-movement of industries is a salient feature of the Indian economy. Co-movement is also observed in the U.S. context (Chang and Hwang, 2015).

	Mean	**Maximum**	**Minimum**	**SD**
Overall	0.32	0.64	0	0.17
IIP Recession	0.45	0.64	0.27	0.15
IIP Expansion	0.28	0.64	0	0.16

Table 7: Diffusion Index

[12] Table 6A (Appendix) lists the turning points of aggregate IIP series at the level form.

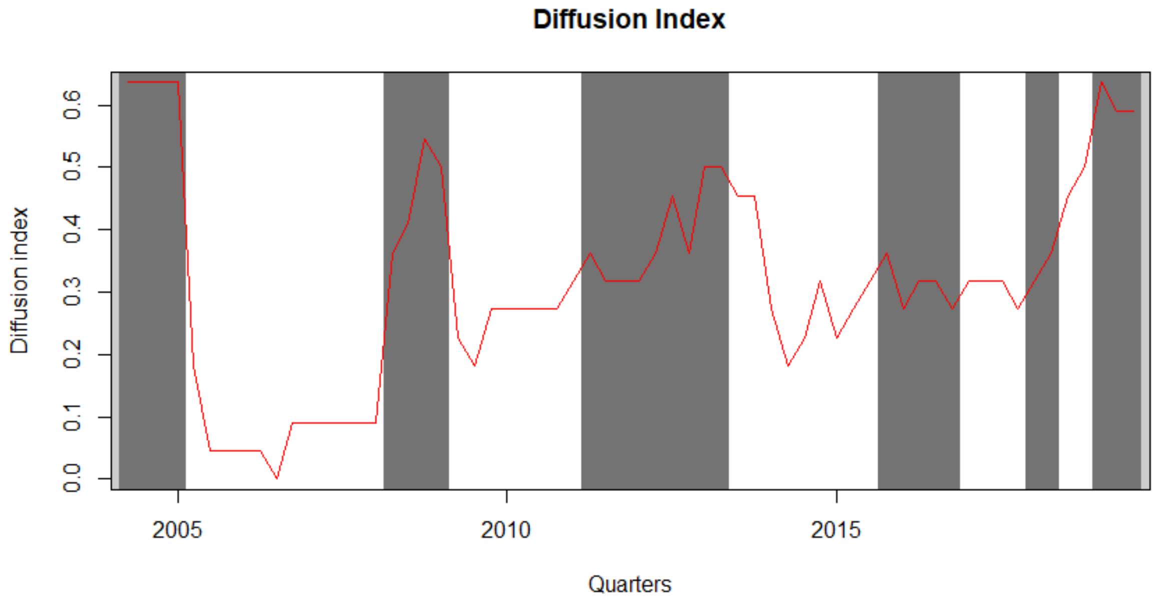

Figure 2: Diffusion index (over time)

Aggregate IIP Series				
Start Date	**End Date**	**Phase**	**Duration (in quarters)**	**Amplitude**
-	2005 Q1	Recession		
2005 Q1	2008 Q1	Expansion	12	17.9
2008 Q1	2009 Q1	Recession	4	19
2009 Q1	2011 Q1	Expansion	8	16.8
2011 Q1	2013 Q4	Recession	9	11.6
2013 Q2	2015 Q3	Expansion	9	6.1
2015 Q3	2016 Q4	Recession	5	7.7
2016 Q4	2017 Q4	Expansion	4	9.8
2017 Q4	2018 Q2	Recession	2	1.8
2018 Q2	2018 Q4	Expansion	2	2.6
2018 Q4	-	Recession		

Table 8: Turning points of IIP Growth cycles[13]

4.2.2 Distribution of turning points

From Table 9, we find that there is a 56% chance of a leading industry in current IIP peak to be a leading industry in the next IIP peak, whereas 44% chance of a leading industry becoming a lagging industry. We observe that the probability for an industry to be in the leading phase drops as

[13] Turning points of disaggregated industrial cycles and aggregate IIP cycles has been given in Table 5A and 6A (appendix).

we compare P2P (peak to peak) with T2T (trough to trough). More generally, we observe that the probability of an industry remaining in the same phase drops as we go from P2P to T2T.

We have used a lead/lag of 8 quarters following Harding and Pagan (2006). If there is a conflict of phase change, i.e., if an industry has multiple peaks or troughs in 8 quarters before/after the aggregate IIP peak or trough, we have used the minimum distance algorithm. If an industry has a peak at 4 lag and at -1 lag, we have taken the -1 lag and termed the industry as a leading industry.

			Previous			
			Leading	Lagging	Coincident	Acyclical
P2P	**Current**	Leading	0.56	0.44	0.22	0.00
		Lagging	0.75	0.25	0.00	0.00
		Coincident	0.29	0.43	0.00	0.29
		Acyclical	0.40	0.20	0.20	0.20
T2T		Leading	0.29	0.43	0.00	0.29
		Lagging	0.40	0.20	0.00	0.40
		Coincident	0.43	0.57	0.00	0.00
		Acyclical	0.29	0.57	0.00	0.14

Table 9: Transition probability

Figure 3 displays the concentration asymmetry of the industries. We observe not much sharp contrast between the shapes of peak and trough clusters across the aggregate IIP lags, with the maximum reached at lag = 0. IIP sectoral peaks are more concentrated in the leads from the aggregate IIP lead date than the troughs. The sectoral troughs are more or less dispersed in the leads and the lags of the aggregate IIP series. Table 5A (appendix) shows less concentration of peaks and troughs after 2011, suggesting some industries continued to do well during the slowdown.

Upon closer inspection of Figure 3, we find that, for troughs, 27% of the industries on average exit simultaneously from the contraction phase at the aggregate IIP trough date. Second, peak clusters are skewed toward lags (of the aggregate IIP Series), whereas trough clusters tend to be uniform. For peaks, about 28% of industries newly enter the contraction phase at the aggregate IIP peak date. For peaks, the sums of the industry fractions over the left and right sides of the cluster are 34% and 59%. In trough clusters, the respective ratios are 42% and 41%.

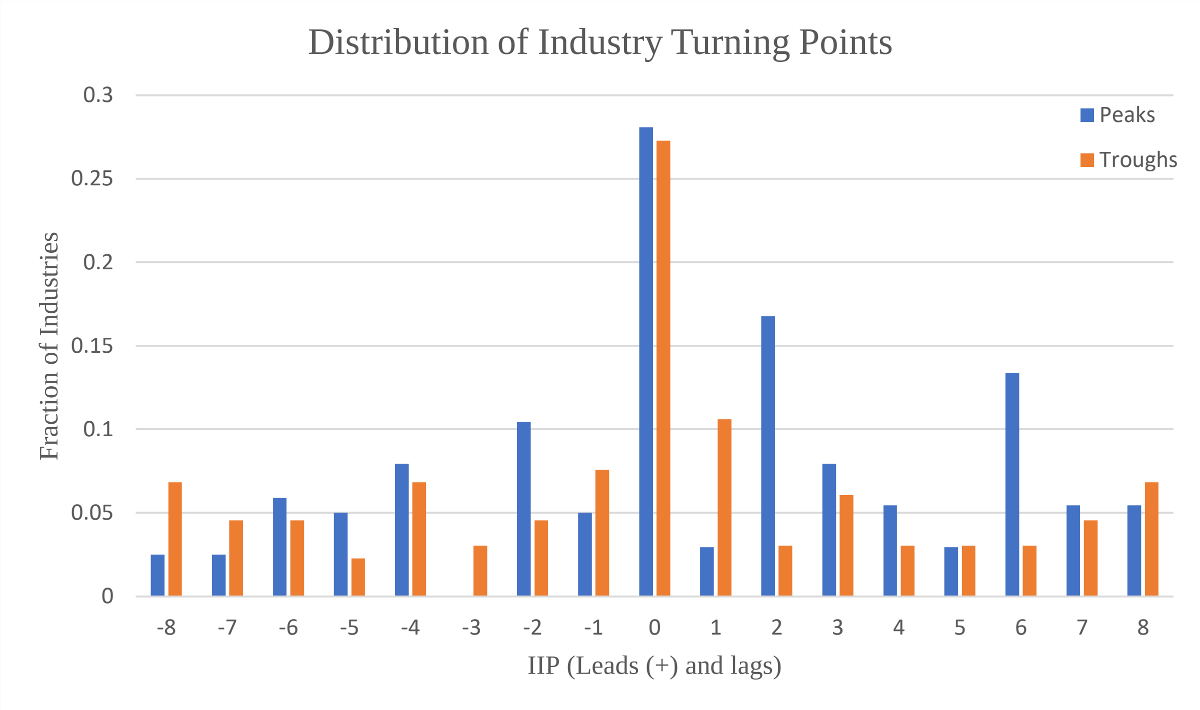

Figure 3: Turning points asymmetry

4.3 Causality

In this section, we present the result of the causality test. We have followed Diebold (2001) and Lemmens et al. (2008) and used the following condition as lag length: $M = \sqrt{T}$ where T is the length of the series. In our paper $M = 10$. The frequency (ω) in the horizontal axis can be translated into a cycle of $T = \frac{2\pi}{\omega}$ quarters. The green line in the graphs denotes 10% significance level, and the red line denotes 5% significance level.

We have used the logarithmic form to examine relationships between IIP growth rate series and exchange rate, M0, M1 and M3. The former has been taken due to the convention regarding usage of the exchange rate in logarithmic form. The logarithmic form is used to bypass the problem of singularity. The level form is used in other relations.

4.3.1 Exchange rate

From Figure 4, we observe that there is evidence of significant causality from exchange rate to basic goods (IIP1) in high frequencies indicating long run cycles whereas there is evidence of reverse causality in lower frequencies indicating short run cycles. There is evidence of medium run cycles from exchange rate to capital goods (IIP2) but no significant reverse causality. For intermediate goods (IIP3), there is evidence of both short run and medium run cycles to exchange rate but no evidence of cycles from the exchange rate to the growth rate of intermediate goods cycle. It is also striking to find evidence of no significant causality from exchange rate to consumer goods (neither for consumer durables nor consumer non-durables). These results indicate some appreciation may help India's investment cycle since capital goods have a large import content.

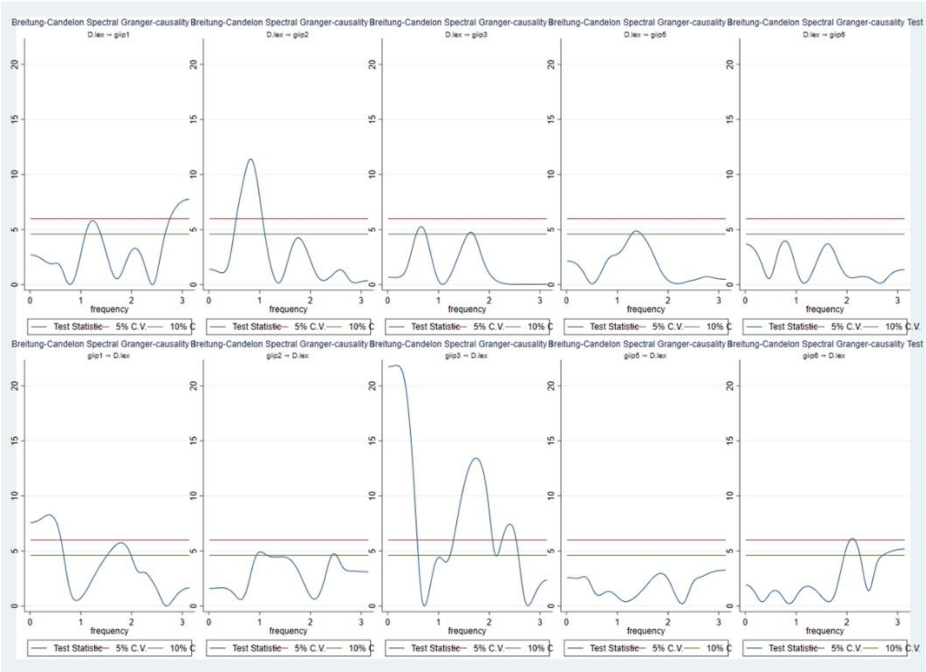

Figure 4: Exchange rate causality

4.3.2 M0

From Figure 5, it is evident that there is significant causality from M0 to intermediate growth rates (at medium frequencies) and consumer non-durables (at higher frequencies) yielding medium run and long run cycles, respectively.

Reverse causality is present from basic, capital and consumer non-durable goods growth rates to M0 at low frequencies whereas, both medium run and long run cycles are generated for consumer durables growth rate to M0.

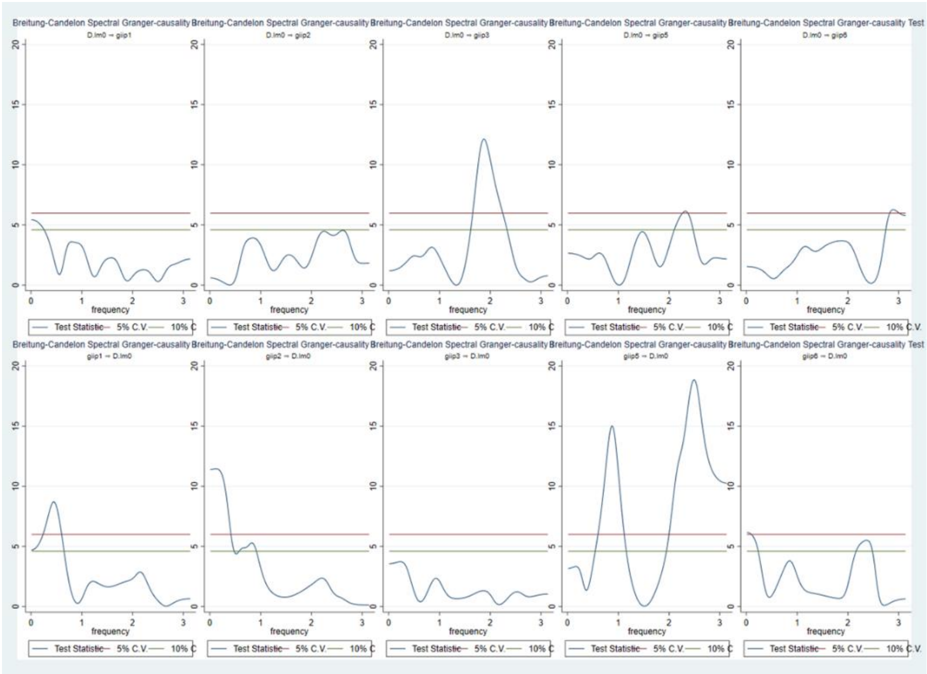

Figure 5: M0 Causality

4.3.3 M1

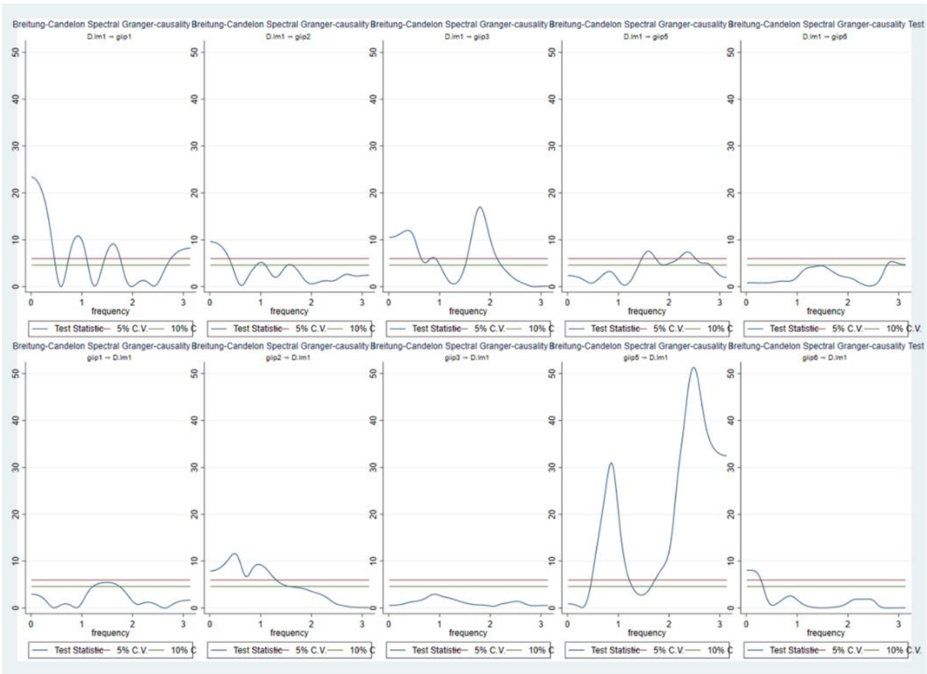

Figure 6: M1 causality

From Figure 6, we observe that M1 causes basic, capital, and intermediate growth rates in low frequencies and medium frequencies whereas for consumer durables, M1 causes medium run cycles. Reverse causality is observed with respect to capital (short to medium run cycles), consumer durables (medium to long run cycles) and consumer non-durables (short run cycles).

4.3.4 M3

There is evidence of short run and medium run cycles from M3 to intermediate growth rate cycles whereas long run cycles are observed for consumer goods growth rate cycles. Reverse causality is present for intermediate and consumer durables (at medium frequencies) and consumer non-durables (at low frequencies).

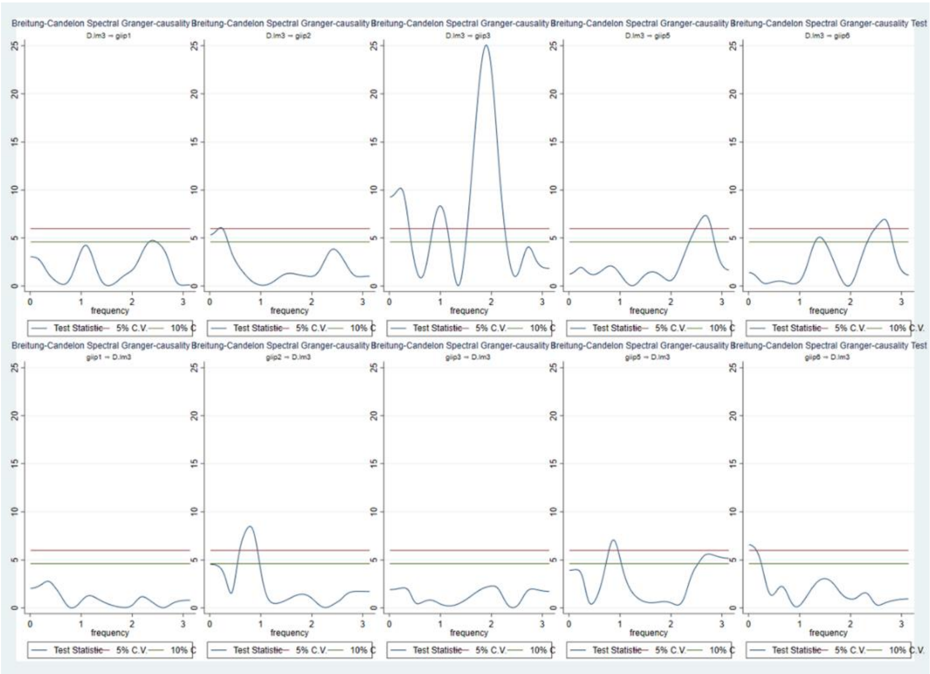

Figure 7: M3 causality

4.3.5 91 days Government securities yield (primary)

Govt. securities yield as the risk-free nominal interest rate is causing capital goods growth rate cycles (at medium and high frequencies) whereas reverse causality occurs at medium frequencies. Causality runs from intermediate growth rate to govt. securities yield at short run and long run cycles. Results are contrasting for consumer goods. Uni-directional causality runs from govt. securities yield cycle to consumer durables (at high frequencies) whereas the causality runs from consumer non-durables to govt. securities rate (at medium frequencies).

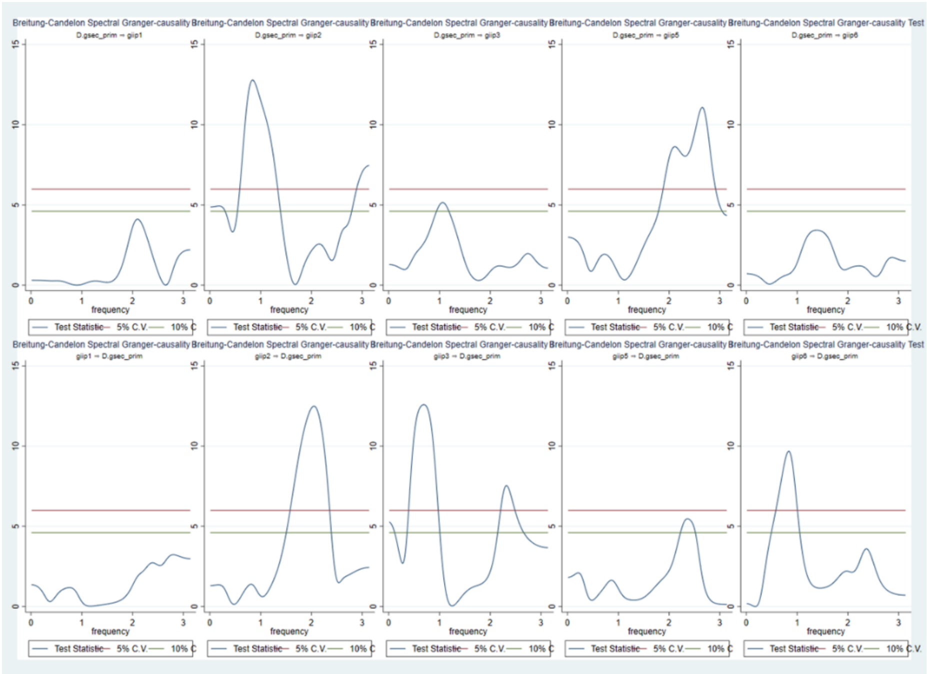

Figure 8: Govt. Sec. yield causality

4.3.6 Realized real interest rate (RRIR)

From Figure 9, we observe that, RRIR significantly causes intermediate growth rate cycles (at medium frequencies) and consumer non-durables (at low frequencies) yielding medium run and short run cycles. However, reverse causality is only for consumer durables causing medium run cycles (of RRIR).

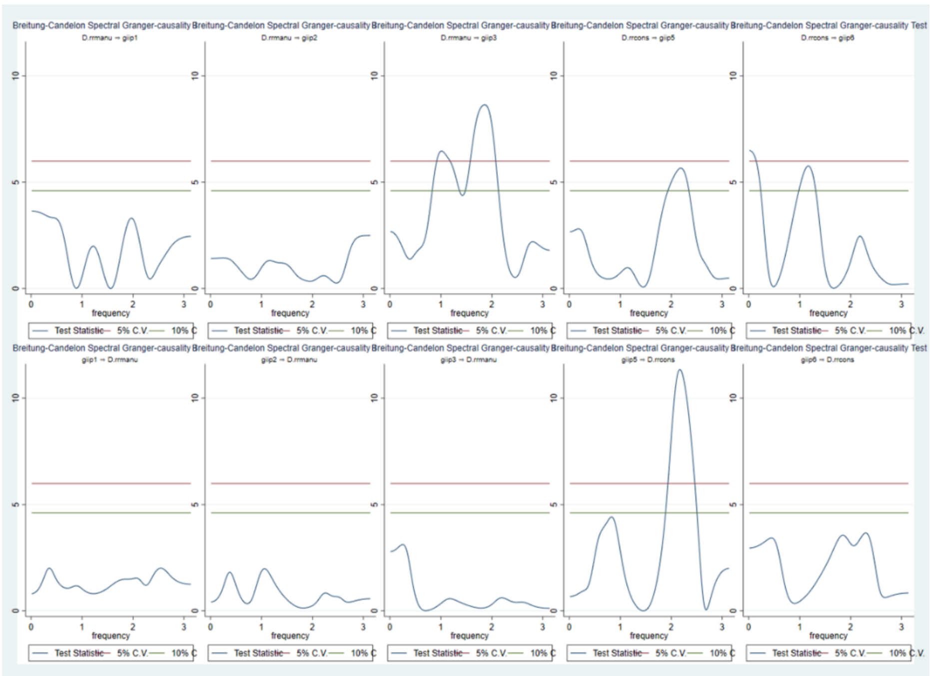

Figure 9: RRIR causality

4.3.7 Government Consumption

Unidirectional causality runs from government consumption to basic goods (at medium frequencies) and from intermediate growth rates and consumer durables to government consumption yielding long run and medium run cycles.

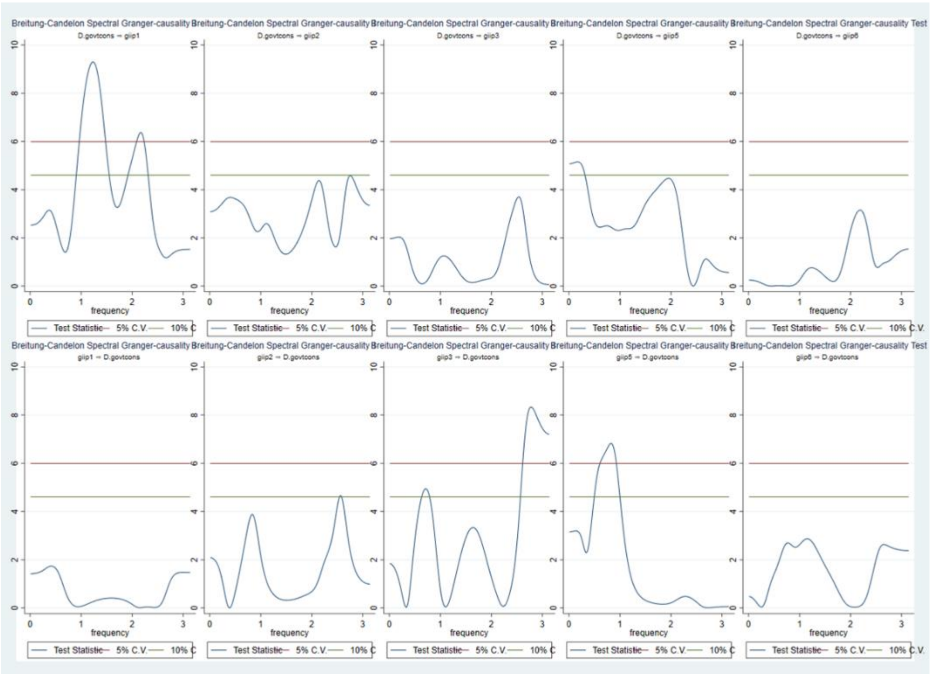

Figure10: Government consumption causality

5. Conclusion

Details of industry business cycles obtained will be useful for policymakers who want to influence them, analysts who want to predict, and researchers who want to understand them. Analysis of industry phase shifts gives more insights and is more robust than the aggregate correlations largely available in the earlier literature on developing economy business cycles.

The analysis establishes that business cycles do exist in India, and are even more pronounced for industry. It is important to make this point because the Indian debate tends to be dominated by growth, development and structural reform. The level of co-movement across disaggregated industry points to some common drivers. As most industry cycles are pro-cyclical counter-cyclical policy becomes all the more important. Causality analysis by industry type shows the impact of many macroeconomic variables. The diversity of the impact points to aspects of Indian macroeconomic structure. Therefore, stabilization policies need to be used more and fine-tuned based on research.

For example, since capital goods are a lead industry and are sensitive to the policy interest rate, timely rate changes are important. Exchange rates also affect their cycles. Another lead sector is basic goods. Here investment by public sector enterprises has a role to play. Expansions are longer for basic goods and they are relatively independent to monetary policy shocks and affected by government expenditure pointing to their stabilizing function. Currency and credit matter for consumer non-durables indicating the importance of maintaining liquidity. Interest rates also affect consumer durables, countering the myth that interest rates do not matter for demand and output because of poor transmission and other issues. They do matter but in combination with currency and credit.

There are specific results on the duration of individual industry cycles, their cyclicality, phase shifts, amplitude, lead-coincident sectors, duration symmetry and co-movement. Since co-movement is greater during troughs, a broad-based upturn is possible in suitable conditions. The exchange rate, currency, credit, nominal and real interest rates all affect industry cycles, but differences in impact by industry type may be due to the structure of the economy with its mix of formal and informal sectors. There is also reverse causality from industry cycles to monetary policy variables. "Cash and credit" is more important for consumer non-durables, while interest rates matter for consumer durables and capital goods. Basic goods are somewhat insulated, except for working capital, perhaps because of more government ownership. The scattered pattern of peaks and troughs after 2013, suggests some industries continued to do well during the post 2011 growth slowdown. Industrial cycles during this period were shallow and short.

Future work includes using more disaggregated industry data. Relatively weak results with RRIR suggest it needs to be calculated using more disaggregated product price series. Causality with other macroeconomic series such as oil price inflation can also be explored.

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Appendix

Names of industries	Basic	Capital	Intermediate	C Durables	C Non-durables
Food Products & Beverages	2.14	-	2.65	-	67.97
Tobacco Products	-	-	-	-	15.7
Textiles	-	-	34.24	2.58	24.82
Wearing Apparel, Dressing and Dyeing of Fur	-	-	-	-	27.82
Luggage, Handbags, Saddlery, Harness & Footwear, Tanning & Dressing of Leather Products	-	-	2.24	-	3.58
Wood & Products of Wood & Cork except Furniture, Articles of Straw & Plating Materials	-	-	10.51	-	-
Paper & Paper Products	-	-	5.81	-	4.18
Publishing, Printing & Reproduction of Recorded Media	-	-	-	0.7	10.09
Coke,Refined Petroleum Products & Nuclear Fuel	36.07	-	31.09	-	-
Chemicals & Chemical Products	31.67	-	28.59	1.17	39.15
Rubber & Plastic Products	-	0.65	9.09	8.24	2.27
Other Non-Metallic Mineral Products	25.18	7.07	5.82	5.07	-
Basic Metals	111.919	-	1.43	-	-
Fabricated Metal Products except Machinery & Equipment	4.92	5.39	12.32	2.96	5.27
Machinery and Equipment nec	-	28.37	4.61	4.66	-
Computer, electronic and optical products	-	3.03	-	0.02	-
Electrical Machinery & Apparatus nec	0.03	15.76	1.96	0.03	2.02
Motor Vehicles, Trailers, Semi-trailers	-	19.91	0.99	19.74	-
Other Transport Equipment	0.17	5.37	0.09	12.62	-
Furniture Manufacturing nec	-	-	-	20.11	9.86
Note: C: Consumer					

Table 1A: 2-digit NIC classification and the respective weights according to usage[14]

[14] The aggregate of the weights equal to 1000.

Type	2-digit IIP (2004 Q2 - 2019 Q3)	HP Filter	CF Filter
	Aggregate IIP	**4**	**4**
Basic	Mining	7.5	5
Basic	Electricity	3.75	3.75
	Manufacturing	3.75	3.75
C non-durables	Food Products & Beverages	3.75	7.5
C non-durables	Tobacco Products	5	5
Intermediate	Textiles	3.75	3.75
C non-durables	Wearing Apparel, Dressing and Dyeing of Fur	7.5	7.5
C non-durables	Luggage, Handbags, Saddlery, Tanning & Dressing of Leather Products	3.75	3.75
Intermediate	Wood & Products of Wood except Furniture, Articles of Straw & Plating Materials	3.75	7.5
Intermediate	Paper & Paper Products	5	5
C non-durables	Publishing, Printing & Reproduction of Recorded Media	5	5
Basic	Coke, Refined Petroleum Products & Nuclear Fuel	5	5
C non-durables	Chemicals & Chemical Products	3	3.75
Intermediate	Rubber & Plastic Products	7.5	5
Basic	Other Non-Metallic Mineral Products	3.75	3.75
Basic	Basic Metals	3.75	3.75
Intermediate	Fabricated Metal Products except Machinery & Equipment	5	5
Capital	Machinery and Equipment nec.	3.75	3.75
C durables	Furniture Manufacturing nec.	7.5	2.5
Capital	Motor Vehicles, Trailers, Semi-trailers	7.5	7.5
C durables	Other Transport Equipment	7.5	3.75
Capital	Computer, electronic and optical products	5	5
Capital	Electrical Machinery & Apparatus nec.	5	5

Table 1A: Duration of the industrial cycles

		HP Filter			CF Filter		
Basic	Mining	0.43	*	Pro	0.15		Acyclical
Basic	Electricity	0.27	*	Pro	0.56	*	Pro
Basic	Coke, Refined Petroleum Products & Nuclear Fuel	0.25	*	Pro	0.43	*	Pro
Basic	Other Non-Metallic Mineral Products	0.42	*	Pro	0.53	*	Pro
Basic	Basic Metals	0.46	*	Pro	0.58	*	Pro
Capital	Machinery and Equipment nec	0.72	*	Pro	0.68	*	Pro
Capital	Motor Vehicles, Trailers, Semi-trailers	0.60	*	Pro	0.52	*	Pro
Capital	Computer, electronic and optical products	0.43	*	Pro	0.35	*	Pro
Capital	Electrical Machinery & Apparatus nec	0.32	*	Pro	0.23	*	Pro
Intermediate	Textiles	0.30	*	Pro	0.70	*	Pro
Intermediate	Wood & Products of Wood & Cork except Furniture, Articles of Straw & Plating Materials	0.45	*	Pro	0.40	*	Pro
Intermediate	Paper & Paper Products	0.10		Acyclical	0.14		Acyclical
Intermediate	Rubber & Plastic Products	0.25	*	Pro	0.01		Acyclical
Intermediate	Fabricated Metal Products except Machinery & Equipment	0.60	*	Pro	0.58	*	Pro
C durables	Furniture Manufacturing nec	0.32	*	Pro	0.10		Acyclical
C durables	Other Transport Equipment	0.37	*	Pro	0.44	*	Pro
C non-durables	Food Products & Beverages	0.54	*	Pro	0.75	*	Pro
C non-durables	Tobacco Products	-0.30	*	Counter	-0.34	*	Counter
C non-durables	Wearing Apparel, Dressing and Dyeing of Fur	0.07		Acyclical	0.31	*	Pro
C non-durables	Luggage, Handbags, Saddlery, Harness & Footwear, Tanning & Dressing of Leather Products	0.26	*	Pro	0.62	*	Pro
C non-durables	Publishing, Printing & Reproduction of Recorded Media	0.18		Acyclical	0.41	*	Pro
C non-durables	Chemicals & Chemical Products	0.36	*	Pro	0.56	*	Pro

Table 2A: Classical correlation of industrial cycles (with aggregate IIP)

		HP Cycle		CF Cycle	
Basic	Mining	0	Coincident	13	Lead
Basic	Electricity	9	Lead	9	Lead
Basic	Coke, Refined Petroleum Products & Nuclear Fuel	14	Lead	1	Lead
Basic	Other Non-Metallic Mineral Products	0	Coincident	0	Coincident
Basic	Basic Metals	9	Lead	10	Lead
Capital	Machinery and Equipment nec	0	Coincident	6	Lead
Capital	Motor Vehicles, Trailers, Semi-trailers	0	Coincident	6	Lead
Capital	Computer, electronic and optical products	1	Lead	12	Lead
Capital	Electrical Machinery & Apparatus nec	0	Coincident	-5	Lag
Intermediate	Textiles	-1	Lag	-1	Lag
Intermediate	Wood & Products of Wood & Cork except Furniture, Articles of Straw & Plating Materials	0	Coincident	2	Lead
Intermediate	Paper & Paper Products	6	Lead	6	Lead
Intermediate	Rubber & Plastic Products	-1	Lag	4	Lead
Intermediate	Fabricated Metal Products except Machinery & Equipment	0	Coincident	7	Lead
C durables	Furniture Manufacturing nec	-11	Lag	-11	Lag
C durables	Other Transport Equipment	13	Lead	6	Lead
C non-durables	Food Products & Beverages	0	Coincident	0	Coincident
C non-durables	Tobacco Products	-1	Lag	-1	Lag
C non-durables	Wearing Apparel, Dressing and Dyeing of Fur	6	Lead	-8	Lag
C non-durables	Luggage, Handbags, Saddlery, Harness & Footwear, Tanning & Dressing of Leather Products	-7	Lag	-8	Lag
C non-durables	Publishing, Printing & Reproduction of Recorded Media	11	Lead	11	Lead
C non-durables	Chemicals & Chemical Products	-1	Lag	-1	Lag

Table 4A: Dynamic correlation (with aggregate IIP) (in quarters)

		2004			2005				2006				2007				2008				2009				2010				2011			
		Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Basic	Coke,Refined Petroleum Products & Nuclear Fuel					T													P			T		P			T			P		T
	Other Non-Metallic Mineral Products				T																											P
	Basic Metals				T																											
	Mining				T																							P				
	Electricity																															
Capital	Machinery and Equipments nec				T												P				T								P			
	Motor Vehicles, Trailers, Semi-trailers				T												P			T												
	Computer, electronic and optical products																		P		T					P		T				
	Electrical Machinery & Apparatus nec			P		T														P												T
Intermediate	Textiles																P		T									P		T		
	Wood & Products of Wood & Cork except Furniture, Articles of Straw & Plating Materials				T														P		T				P			T				P
	Paper & Paper Products										P		T									P		T								
	Rubber & Plastic Products																											P		T		
	Fabricated Metal Products except Machinery & Equipment				T												P				T											P
Durables	Furniture Manufacturing nec			T			P			T								P			T		P									T
	Other Transport Equipment			T									P		T																	P
Non-durables	Food Products & Beverages				T												P				T											
	Tobacco Products				T						P						T				P								T			
	Wearing Apparel, Dressing and Dyeing of Fur				T												P															
	Luggage, Handbags, Sadlery, Harness & Footwear, Tanning & Dressing of Leather Products			P			T										P				T											
	Publishing, Printing & Reproduction of Recorded Media																		P			T										
	Chemicals & Chemical Products					T									P					T			P		T				P			T
Aggregate IIP					T												P				T											

		2012				2013				2014				2015				2016				2017				2018				2019		
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
Basic	Coke,Refined Petroleum Products & Nuclear Fuel							P			T																P					
	Other Non-Metallic Mineral Products			T							P			T				P				T							P			
	Basic Metals				P		T								P		T															
	Mining						T									P		T														
	Electricity																											P		T		
Capital	Machinery and Equipments nec							T						P			T								P		T		P			
	Motor Vehicles, Trailers, Semi-trailers	P								T																	P					
	Computer, electronic and optical products		P										T														P					
	Electrical Machinery & Apparatus nec															P			T			P						T				
Intermediate	Textiles																								P							
	Wood & Products of Wood & Cork except Furniture, Articles of Straw & Plating Materials									T					P									T								
	Paper & Paper Products																		P													
	Rubber & Plastic Products		P						T					P		T						P										
	Fabricated Metal Products except Machinery & Equipment								T		P			T					P				T			P						
Durables	Furniture Manufacturing nec				P				T							P			T			P		T		P						
	Other Transport Equipment			T								P			T					P		T							P			
Non-durables	Food Products & Beverages				P				T			P								T												
	Tobacco Products																	P								T			P			
	Wearing Apparel, Dressing and Dyeing of Fur	T					P		T														P		T							
	Luggage, Handbags, Sadlery, Harness & Footwear, Tanning & Dressing of Leather Products					P		T						P										T			P		T			
	Publishing, Printing & Reproduction of Recorded Media	P																T						P								
	Chemicals & Chemical Products								P				T																			
Aggregate IIP																P					T											

Table 5A: Peaks and troughs for each individual industry

Aggregate IIP Series		
Start Date	**End Date**	**Phase**
	2005 Q1	Recession
2005 Q1	2008 Q1	Expansion
2008 Q1	2009 Q1	Recession
2009 Q1	2015 Q3	Expansion
2015 Q3	2016 Q4	Recession
2016 Q4		Expansion

Table 6A: Turning points of Aggregate IIP Series