Measuring business cycle conditions in India

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Radhika Pandey, Ila Patnaik and Ajay Shah

National Institute of Public Finance and Policy
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Radhika Pandey* Ila Patnaik Ajay Shah

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Abstract

We develop a measure of business cycle conditions at a quarterly frequency – the coincident indicator – that better utilises the limited data resources available in India. The new indicator has a historical time series from 1999 onwards. The methods used here feature numerous improvements upon previous work in the field.

*We thank Pramod Sinha for valuable inputs into this work. The views expressed in this paper are the authors' personal opinion.

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Box 1: Research program on Indian business cycles

1. Patnaik and Sharma (2002) worked out dates for business cycle recessions, in the pre-liberalisation period, using annual GDP data. It then constructed a composite coincident indicator using the quarterly GDP series as the reference series.
2. Ghate et al. (2013) presented the business cycle stylised facts for the Indian economy from 1950 to 2010.
3. In Bhattacharya et al. (2016), we established procedures for seasonal adjustment of time series.
4. In Pandey et al. (2017), we arrived at dates for the old GDP series for the 1996-2014 period.
5. In Pandey et al. (2019), we presented a historical account of the business cycle chronology for the Indian economy, and describe the economic conditions that shaped the nature of cycles in the pre and post liberalisation period.

1 Introduction

Business cycle analysis has become more important in India. In the pre-liberalisation period, the Indian economy was driven primarily by short-lived monsoon and oil shocks (Patnaik and Sharma, 2002; Shah, 2008). After 1991, structural transformation and greater market orientation have led to the emergence of a more conventional investment-inventory cycle, that is related to the mainstream conception of business cycles (Ghate et al., 2013). Business cycle measurement is, then, particularly important for the recent decades.

At the essence of the notion of a business cycle is a shared movement in a large number of macroeconomic series. The GDP growth rate alone – even if adequately measured in terms of timeliness and reliability – does not suffice in identifying the state of the business cycle.

This paper builds on a research program on Indian business cycles that began in 1996 (See Box 1). In this paper, we carry this research program forward to forming a composite coincident indicator for the Indian economy for the post liberalisation period. We build on the pioneers of business cycle measurement in India (Mall, 1999; Chitre, 2001; Dua and Banerji, 1999, 2001). We improve upon their work in four respects: (a) A shift from annual to quarterly data, (b) with a larger number of well measured macroeconomic series, (c) sound statistical procedures for seasonal adjustment, and (d) improved statistical procedures for the classification of indicators and aggregation into an index.

The standard techniques in business cycle measurement, which are employed worldwide, run through the following steps:

1. A reference series, typically GDP, is chosen, and a dating of the business cycle is obtained.

2. A large database of well measured time-series is constructed. On one hand, this database should be as large as possible, but at the same time, many elements of the Indian statistical system yield poorly measured time-series and judgement has to be exercised in avoiding these.

3. Seasonal adjustment is performed for all these series.

4. Each of the series is classified as being ‘leading’, ‘lagging’ or ‘coincident’ depending on whether turning points appear before, with or after the turning points in the reference series.

5. The group of indicators which are coincident are combined into a coincident index, and the group of indicators which are leading are combined into a leading index.

In India, there are now 72 quarterly time series with fairly sound measurement for the period from 2005 to 2018, and 67 time series for the period from 1999 to 2018.

The changes in the methodology for GDP measurement, by the Central Statistical Organisation in 2015, have engendered an expert debate on national income measurement (Nagaraj, 2015; Sapre and Sinha, 2016; Sengupta, 2015). This has increased the relevance of the present study. The coincident indicator that is developed here can yield a useful measure of the state of the business cycle, without relying on GDP data.

The remainder of this paper is structured as follows: Section 2 presents the motivation for constructing coincident indicators especially in reference to an emerging economy like India. Section 3 describes net sales as a reasonable reference series in the absence of a reliable GDP series. Section 4 details the methodology used to identify the coincident series and their aggregation into an index. Section 5 describes the application of these methods towards construction of a coincident index for India. Section 6 shows how the span of data influenced our methods. Section 7 concludes the paper.

2 The coincident indicator

GDP is an important measure of economic activity, but it is released with a considerable lag. The coincident indicator aims to provide a more timely indication of economic activity.

In an advanced economy, GDP is reasonably well measured. Business cycle measurement, nevertheless, pursues the construction of a coincident index, on the grounds that GDP fluctuations can sometimes reflect one-off phenomena, and business cycle phenomena are best seen as the co-movement across a large number of series. The coincident indicator, a tool for aggregation of many macroeconomic series, would in general better reveal business cycle conditions when compared with GDP.

While this is widely used in advanced economies to gauge the state of economic activity (Gillitzer et al., 2005; Graff and Etter, 2004), the application in emerging economies is limited owing to the lack of databases of historical time series (Mongardini and Saadi-Sedik, 2003). However recent studies have begun to analyse the stylised facts of business cycles in emerging and developing markets, and construct coincident and leading indicators (de Cabo Verde, 2012).

In a setting like Turkey, China or India, there are concerns about GDP measurement itself (Sengupta, 2015; Sapre and Sinha, 2016; EPW, 2015; Nagaraj, 2015). Here, there is an additional motivation in favour of constructing a coincident index, as this can be a useful output proxy, which can read the evolution of the economy when GDP is not well measured.

Our work here is analogous to the 'Li Keqiang index' which is used in China in response to concerns about GDP measurement. When compared with this index, however, our methods are located in mainstream tools for business cycle measurement while the Li Keqiang index is an ad hoc measure.

GDP growth is widely viewed as the single summary statistic that portrays business cycle conditions. The coincident indicator is expected to better reveals business cycle conditions for three classes of reasons: (a) Measurement error of GDP data (b) Timeliness of GDP data (c) One-off difficulties in GDP numbers which are avoided by going to the first principles of business cycle theory, the idea that the business cycle is the co-movement seen in a large number of macroeconomic time series. These three issues motivate our work on the coincident indicator.

3 Choice of the reference series

The reference series is a summary measure about the business cycle conditions in the economy. Any system of business cycle analysis has to start at choosing a reference series, and establishing a chronology of its turning points. Coincident, leading and lagging indicators are then defined with reference to the cyclical turning points of the reference series.

There is a literature that has constructed the coincident indicator for India (Mall, 1999; Dua and Banerji, 1999, 2001; Patnaik and Sharma, 2002). Most of these studies focus on the pre-liberalisation period. There are a few studies which work on the post liberalisation period (Dua and Banerji, 2006; RBI, 2006). These papers use GDP, GDP excluding agriculture, or IIP as the reference series.

Alternative 1: GDP. GDP is an obvious choice for a reference series as it measures the total output of the economy. If agriculture and government are excluded from GDP, this would yield a good measure of the private economy that is unaffected by weather shocks or government policy decisions. However, given the difficulties of GDP measurement in India, there is a concern that flaws in GDP (if chosen as the reference series) would propagate into flaws in the resulting coincident indicator.

Alternative 2: IIP. In the international literature, the index of industrial production is widely used as a measure of business cycle conditions.[1] Pandey et al. (2017) find that the turning points chronology of IIP is broadly similar to the old GDP series. However, the IIP is of limited value in India, as manufacturing is a small part of the economy. In addition, the IIP has significant difficulties of measurement (Nagaraj, 1999, 2002). Recently the IIP series also underwent a base year change, and a consensus has yet to emerge about the quality of measurement.

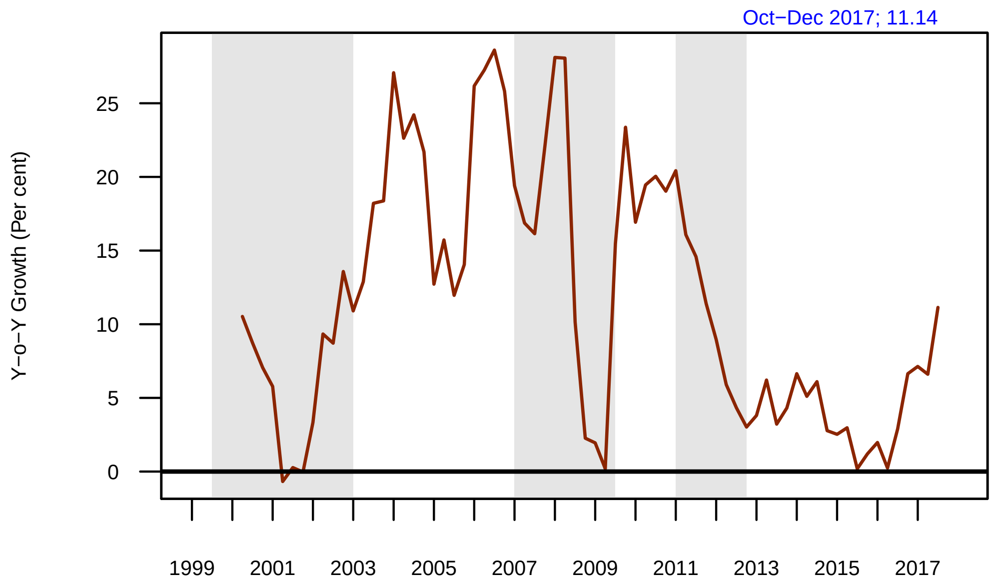
Alternative 3: Net sales of listed companies. A third option could be to construct a reference series from the results reported by all listed companies each quarter. We construct an index of the net sales of listed firms (Dua et al., 2013). This works with the listed firms observed in the CMIE Prowess database. Finance companies are excluded as there are concerns about the comparability of their accounting data. Oil companies are excluded as their revenues jump around sharply with global crude oil prices and Indian policy decisions on administered prices which yields fluctuations that do not reflect domestic business cycle conditions.

The methodology of index constructions looks at each two consecutive quarters, identifies a panel of firms observed in both quarters, and works out the percentage change in the sum of net sales across all the firms observed. These percentage changes are cumulated to construct a net sales index. This index

[1] Until 2012, the OECD system of composite leading indicators used the IIP as a reference series for most countries, which is available on a monthly basis and displayed strong co-movements with GDP. Since April, 2012, they have switched to GDP as the reference series. See `http://www.oecd.org/sdd/leading-indicators/49989659.pdf`

Figure 1 Year-on-year growth in net sales

The figure shows the year-on-year growth in net sales of non-oil, non financial firms. The shaded region shows the periods of recession *identified using the old GDP series*. Three episodes of recession are identified: 1999 Q4-2003 Q1, 2007 Q2-2009 Q3, and 2011 Q2 to 2012 Q4. The trajectory of net sales index conforms with the turning points identified using GDP series. We see a decline in the growth of net sales index during the identified periods of recession using the old GDP as the reference series.



proves to correlate well with the old GDP series.

Figure 1 shows the year-on-year growth of this quarterly time-series. Pandey et al. (2017) find that the periods of recession identified in the net sales index are broadly in conformity with the recession periods using the old GDP data (2004-05 base year) as the reference series.

4 Methodology for identifying coincident series

No single indicator can be considered as a reliable proxy of business cycles at all times. At the essence of business cycle research is the idea of monitoring a large variety of indicators, where the turning points coincide with the reference series. As Burns and Mitchell (1946) say:

> Our definition presents business cycles as a consensus among expansions in 'many' economic activities, followed by similarly generalised recessions, contractions and revival.

Thus, we seek to identify many series which are coincident with the reference series. The ideal choice of a coincident series would be one which shows the same turning points as the reference series and exhibits high cross-correlation with the reference series. Before we get to the identification of coincident series, we need to pre-process the data.

4.1 Standardisation and filtering of series

The first step involves selecting a set of variables and standardising them (Pandey et al., 2017).

1. Selection of indicators: The selection of candidate series for coincident analysis is based on certain criteria:
   (a) Frequency: We require quarterly frequency data, with adequate span. Some important new measures are now available, such as monthly labour market data, but they are only observed for a few years and thus must be excluded from this analysis.
   (b) Economic significance: The timings of cyclical upswings and downswings must be economically logical.
   (c) Data quality: Each of these series must have information gathering and processing in a statistically reliable way. We have studied the underlying methods used by all available time-series in India, which are visible at a quarterly frequency, and chosen a subset that appears to have sound measurement.
2. Seasonal adjustment of candidate series and adjustment for outliers. We build on our work in Bhattacharya et al. (2016). Alongside the construction of seasonally adjusted data, we ensure careful treatment of extreme values, which improves the robustness of the resulting coincident indicator.

3. Extraction of cycles: The next step involves determination of the concept of a *cycle* in each series. The classical definition of business cycles, used by the NBER, refers to the determination of turning points in the *level* of economic activity. In the Indian setting, it is more useful to think in terms of a *growth cycle*. Business cycles fluctuations are then understood as deviations from the trend of the series. Since we do not see an absolute decline in the *level* of series in our dataset, we use the growth cycle approach to identify cyclical fluctuations.

   The next step lies in decomposing each series into the trend and the cycle (Hodrick and Prescott, 1997; Baxter and King, 1999; Christiano and Fitzgerald, 2003). For many years, the Hodrick-Prescott ("HP") filter was used for this purpose. However, recent discoveries have shed new light on the difficulties associated with the HP filter (Hamilton, 2017). A key concern for our purposes lies in the fact that the HP filter calculates the cyclical component based on the future values. As a result, it might introduce autocorrelation into the cyclical component of the series, even if it is not present in the data generating process.

   Hence, we use the Christiano-Fitzgerald (CF) filter to decompose each series into its trend and cyclical component. The CF filter, like the Baxter-King filter, belongs to the category of band-pass filters. Band-pass filters eliminate slow moving trend components (such as the overall trend GDP growth, and inflation, of the economy) and high frequency components (the day to day shocks) while retaining the fluctuations of intermediate frequencies, which are the business cycle fluctuations. Such frequency domain filtering is ideal for the business cycle analysis of continuous and infinitely long time series. In the real world, the observed time series are discrete and finite. The CF filter has good properties; it approaches the ideal filter as the sample size approaches infinity. Technical details on the CF filter are placed at Appendix D.

   Using the CF filter requires taking a stand on what are business cycle frequencies. We use the NBER definition: from 8 to 32 quarters (King and Watson, 1996). For comparability across a number of series, the cyclical component is normalised by subtracting the mean of the cyclical component from it and dividing by the absolute standard deviation of the cyclical component.[2]

Our entire dataset, of 72 quarterly series, is put through this pre-processing as is the reference series.

4.2 Selection of coincident indicators

We now seek to identify which of the series in the dataset are coincident with the reference series.

4.2.1 Cross-correlations

Cross-correlations are a useful tool to analyse the co-movement between the candidate and the reference series (Iacoviello, 2001). Cross-correlations between the lagged cyclical component of the candidate and the reference series are calculated. The lag at which the cross-correlation has the largest value tells us about the average lead (or lag) of the candidate series over the reference series. We pick those variables as coincident where the highest correlation between the reference series and the the candidate series is seen at the contemporaneous period.

4.2.2 Harding-Pagan Index of Concordance

Cross-correlations analyse the variable y_t itself, but Harding and Pagan (2002) point out merits in studying the properties of the *phase* variable S_t associated with each candidate series. Harding and Pagan (2006) measure the degree to which two business cycles are in sync by the percentage of

[2]Some papers modify the upper or lower bound of the length of the cycle. For example Agresti and Mojon (2001) allow the upper bound on the length of the business cycle to be 40 quarters (10 years) instead of 32 quarters (8 years) depending on the observed length of the business cycle in European countries. In our experience, the Indian business cycle plays out over the 8–32 quarter range.

time the two variables are in the same phase. This involves identification of turning points in the cyclical component of candidate series.

The standardised cyclical component forms the input series for the application of the dating algorithm by Bry and Boschan (1971). The Bry and Boschan (1971) algorithm is based on a standardised set of rules that facilitate comparison of business cycle turning points across countries, regions and time-periods. The procedure was subsequently improved by Harding and Pagan (2002). Appendix E shows the rules to identify turning points.

Once the turning points are identified for our dataset, we construct the state variable S_t for each of the series. S_t is a binary variable defined as 0 when the series y_t (in our case the cyclical component) moves from peak to trough and 1 when y_t moves from trough to peak. The advantages of studying S_t over y_t are the binary definitions of recession/expansion assumed by most loss-averse agents, as well as the added ability to test for synchronisation across cycles (Harding and Pagan, 2006).

S_t can be studied in two ways. The first is the Harding-Pagan Index of Concordance (HP index), which measures the proportion of the time the two variables are in the same state. Assuming two variables x and y over N time periods, the index of concordance between them would be I_{xy}, defined in Equation 1:

$$I_{xy} = \frac{\#[S_{xt} = 1, S_{yt} = 1] + \#[S_{xt} = 0, S_{yt} = 0]}{N} \tag{1}$$

The value of the Harding-Pagan index ranges between 0 and 1. An index value of close to 1 indicates perfect procyclicality while an index value of 0 indicates perfect counter-cyclicality. However, given the markov-transition probability structure of recessions ($Pr(S_{t+1} = 0, S_t = 0) \gg Pr(S_{t+1} = 0, S_t = 1)$), there is extensive serial correlation in the S_t series (Harding and Pagan, 2006). Also, since the data duration is very short, the chances of a prolonged expansion or recession in one of the series skewing the value of the index are non-zero.

To correct for these flaws, through the second approach, Harding and Pagan (2006) demonstrate that the following relationship holds between the correlation coefficient ρ^{xy} between S_x and S_y and I^{xy}, which implies that the properties of ρ^{xy} are symmetric to that of I^{xy}:

$$I^{xy} = 1 + 2\rho^{xy}\sigma_{Sx}\sigma_{Sy} + 2\mu_{Sx}\mu_{Sy} - \mu_{Sx} - \mu_{Sy} \tag{2}$$

To estimate the correlation coefficient ρ^{xy}, we use the following OLS estimation:

$$\frac{S_{yt}}{\sigma_{\hat{S_{xt}}}\sigma_{\hat{S_{yt}}}} = A + \rho_{xy}\frac{S_{xt}}{\sigma_{\hat{S_{xt}}}\sigma_{\hat{S_{yt}}}} + \epsilon_t \tag{3}$$

where $\sigma_{\hat{S_{yt}}}$ denotes the sample standard deviation of S_{yt}. Given that ϵ_t inherits the serial correlation in S_t, we use p-values for the Heteroskedasticity-Autocorrelation (HAC) corrected t-statistics for $\hat{\rho_{xy}}$.

4.3 Aggregation of the chosen series

The final step involves the aggregation of the identified series into an index. Combining selected indicators into a composite index helps in reducing spurious signals that may show up in any of the individual components. This is akin to the gains from diversification in a portfolio, or the gains from a combination of forecasts.

We use the Conference Board methodology (Conference Board, 2000). This penalises individual indicators for their volatility. It weights information in coincident series with equal weights, controlling for the fact that different series may carry different information depending on their variance. Our version of their methods uses the more robust scale estimator, the IQR instead of the sample standard deviation. The steps are as follows.

- Calculate the percent changes r_{it} for each series

- Compute the standardisation factor w_i using the inverse of the *interquartile range*.[3] $w_i = \frac{1}{IQR(r_i)}$. Normalise the standardisation factors such that their sum equals one.
- Adjust the percent changes by multiplying them by the component's standardisation factor $s_t = r_{t \times n} w_{n \times 1}$
- Add the adjusted percent changes across the components for each quarter.
- Compute the preliminary levels of the index using symmetric percent change formula. Fixing the initial value of Index I_1 as 100, index values for any time period $t \neq 1$ can be calculated as:

$$I_t = I_1 \Pi_{i=2}^{t} \frac{200+s_i}{200-s_i}$$

- Rebase the index to average 100 in the base year.

5 Applying these methods for India

5.1 Adaptations of the methods that better suit Indian conditions

On one hand, there is a well established global literature which establishes methods for construction of the coincident indicator. At the same time, at many steps in this journey, we have adapted the methods and made methodological decisions which are better suited to Indian conditions.

Under Indian conditions, the span of the data is short, which hampers statistical precision. In addition, while we choose candidate series that we consider well measured, all in all, the Indian statistical system remains weak and there is likely to be measurement error. We have brought in elements which seek to mitigate these problems.

[3] The Conference Board (2000) uses the standard deviation as a measure of volatility.

1. We work with quarterly rather than monthly data as a well measured reference series at a monthly frequency is not available.
2. The reference series is constructed from the quarterly accounting data of listed companies, so as to avoid the potential difficulties associated with the GDP and IIP data.
3. We utilise the robust statistics capabilities of seasonal adjustment tools, so as to diminish the extent of influential observations right there.
4. We replace standard deviations by inter-quartile ranges, so as to reduce the influence of outliers.
5. When faced with two sets of candidate coincident series, obtained through cross-correlation analysis and through the Harding-Pagan methods, we proceed with the set union of these series. This is motivated by the gains from diversification; it is better to use a linear combination of a larger number of series and thus avoid the idiosyncratic problems of any one series.

5.2 Dataset

We use 72 quarterly series as candidate series for the composite coincident index. Owing to data limitations, we work for the period from 2005 Q2 to 2016 Q4. In addition to the macroeconomic series on production, monetary policy, external sector, fiscal policy and financial markets, our dataset also includes indicators of firm performance from CMIE Prowess database and investment project-level indicators from CMIE CapEx database. Appendix F shows the list of the candidate series.

5.3 Identification of coincident series

We test each of the candidate series for seasonal patterns and adjust them for seasonal fluctuations and extreme values. We extract the cyclical component

Table 1 Coincident indicators identified using cross-correlation and Harding-Pagan Index of Concordance.

This table shows the coincident variables identified using the two methods described above. Criterion I identifies the variables based on the maximum correlation with the reference series at the contemporaneous period. Criterion II identifies coincident series based on the Index of Concordance. We do see some similarities in the candidates for coincident series identified through the two criteria. The trade related series figure in criterion I as well as criterion II.

Criterion 1	Criterion 2
Exports	Exports
Non-oil imports	Non-oil imports
Private announced projects	Private announced projects
Non food credit	Air traffic
Steel production	Foreign tourist arrivals
Electricity requirement	
Under-implementation projects in infrastructure	

of the reference and the candidate series through the CF filter. We compute the cross-correlations up to ±5 lags for all the candidate series with the reference series. Table 4 in Appendix A reports the cross-correlation of the cyclical component of the candidate series with the cyclical component of the reference series (the index of net sales).

We identify those variables where the highest correlation observed proves to be in the contemporaneous period.[4]

The second approach to identify coincident series is based on the Harding-Pagan Index of Concordance and the correlation between the state variables of the reference and each of the 72 series. Given the short time-series, we find that a sample correlation of 0.55 and above is statistically significantly different from 0. Table 5 in Appendix B reports the Index of Concordance between the reference and the candidate series.

Table 1 shows the coincident series identified through the two criteria described above. The first three series are identical: exports, non-oil imports

[4]We also explored an alternative approach in which we identify those variables that show high correlation (above a threshold) at the contemporaneous period but not at a lead and lag of one quarter. The variables identified through this approach prove to be a subset of those identified using the above approach.

and private announced projects. In the other series chosen, the two methodologies diverge.

We might have expected project *announcements* to be a leading indicators: with a lag, this would translate into investment activity and thus impact upon aggregate demand. The logic at work here may be more directly based on capacity constraints. Private firms may announce projects when they see existing capacity being fully utilised; thus announcements prove to be coincident.

At this point, we could think of two different coincident indicators: one that is constructed using the series identified using the cross-correlation and another that is constructed using the series identified using the Harding-Pagan estimator. It is important to remember that at the outset, we had a limited dataset to work with, of only 72 indicators. If a coincident indicator contains very few time-series, it is more vulnerable to idiosyncratic features of any one time-series. As an example, when the Indian government introduced a tariff on steel, this would yield greater steel production, and vice versa: this is a phenomenon that affects steel but does not reflect business cycle conditions. Similarly, a terrorist attack or geopolitical tensions may deter foreign tourist arrivals.

In order to obtain greater gains from diversification, we choose to proceed further with the set union of the two sets of indicators. Hence, in the remaining work in this paper, we work with nine series:

1. Exports,
2. Non-oil imports,
3. Production of steel,
4. Electricity requirement,
5. Foreign tourist arrivals,
6. Air traffic,
7. Private sector announced projects,

8. Under-implementation projects in infrastructure,
9. Non-food credit.

The coincident indicator will be an aggregation of conditions as seen in these nine series.

5.4 Aggregation of variables into the coincident indicator

Once we identify a set of coincident series, the next step is to aggregate them. Following the growth cycle approach, we are interested in knowing the extent of deviation of the coincident index from its trend. Thus, we present the aggregate of the *cyclical* components of the chosen series. Towards this, we follow the following steps:

- We de-trend the chosen series using the Hamilton filter.[5]
- We apply the Conference Board methodology to then aggregate the cyclical candidate coincident series into an index. The aggregate measure is expressed as a cyclical component (deviation from the trend in per cent). In order to obtain more robust results, we use the inter-quartile range (IQR) in the place of the standard deviation as a measure of volatility.
- This yields an assessment of the state of the economy as a percentage deviation from trend.

Table 2 shows the weights of the component series. The weights shown are in proportion to the inverse of the IQR for each component series. These are then normalised to sum to one. Figure 2 shows the coincident index (cycle) constructed superposed with the Hamilton filtered net sales index. The figure shows that our coincident cycle is able to track the upswings and downswings in the cyclical component of the reference series.

[5]See Appendix C for an overview of the Hamilton approach to calculate the cyclical component of a series.

Table 2 Weights of the component series based on the inverse of volatility (inter-quartile range)

This table shows the weights and normalised weights of the component series arrived at using the two criteria. The weights are proportional to the inverse of the inter-quartile range. These weights are then normalised to sum to 1. As an example, we see that electricity requirement has the largest weight in the coincident index.

	Weights	Normalised weights	Variables
1	0.04	0.05	Exports
2	0.11	0.13	Production of steel
3	0.15	0.20	Electricity requirement
4	0.10	0.12	Foreign tourist arrivals
5	0.09	0.11	Air traffic
6	0.04	0.05	Non-oil imports
7	0.05	0.06	Private announced projects
8	0.07	0.09	Infrastructure under-implementation projects
9	0.14	0.18	Non-food credit

Figure 2 Superposing coincident index (cycle) with the reference series

This figure shows the superposed plot of the coincident index (cycle) along with the cyclical component of the reference series. The cyclical component of the component series and the reference series is arrived at using the Hamilton filter.

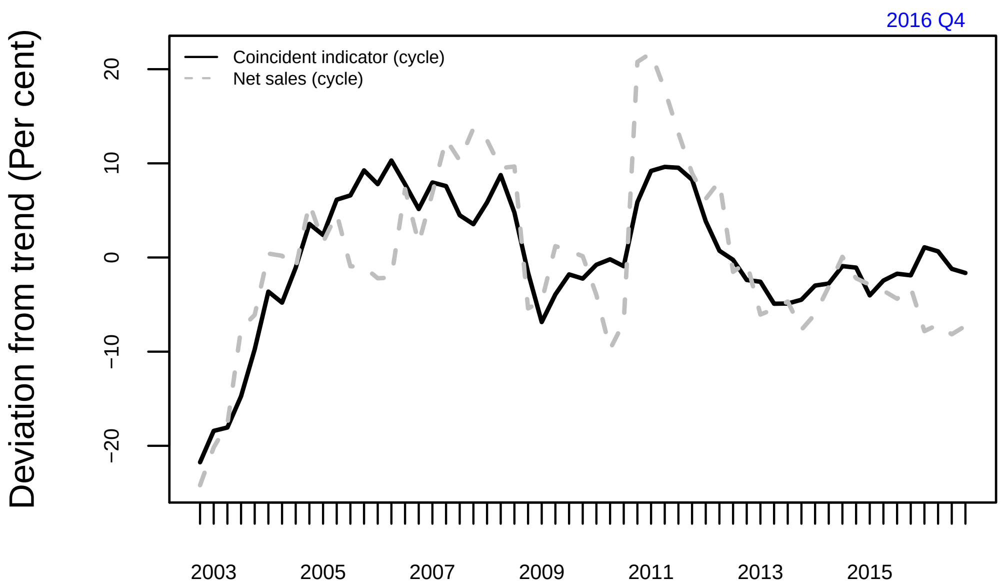


Table 3 Year-on-year growth rate versus the cyclical component

	Exports: Raw series	Exports: YoY	Exports: SA	Exports: Cycle (Deviation from trend (Per cent))
2008 Q1	47088.20	37.30	45748.72	19.77
2008 Q2	56326.90	60.78	55943.26	37.46
2008 Q3	52578.00	40.13	51991.26	23.48
2008 Q4	38659.30	-3.79	40480.04	-0.77
2009 Q1	37727.20	-19.88	37067.32	-13.64

5.5 Calculation of coincident indicator: An example

Table 3 presents a comparison between the conventionally observed year-on-year growth; and the Hamilton filtered cyclical component for exports for the period 2008 Q1 to 2009 Q1. The year-on-year growth is computed from the raw series (shown in column 1). The raw series and the year-on-year growth show a sharp decline in exports in the global financial crisis. Now we introduce our methods. We first adjust the raw series for seasonality. The series adjusted for seasonality is shown in column 3. The cyclical component (Column 4) is extracted from the seasonally adjusted series. The cyclical component is one of the inputs in the construction of the coincident indicator. The weight of the exports series in the coincident indicator is shown in Table 2.

6 Choosing an optimum span of data

Making decisions about the span of the data forms an integral part of our analysis. There are 72 quarterly time-series with sound measurement. These are available for a relatively short span i.e. starting from from 2005. If we push the span backwards to 1999, we are left with 67 quarterly time-series with sound measurement. Since we have a limited dataset to work with, we sacrifice on the span. In the first step of identifying the candidate coincident series, we work with the 72 series available from 2005. It turns out that the identified nine series are available from 1999. So we are permitted to analyse the constructed coincident indicator from 1999.

The span question also gains prominence in the choice of the detrending filter. While the Hamilton's approach to extract the cyclical component is more popular and addresses some of the criticisms of the widely used Hodrick-Prescott filter, we tend to lose some observations with its application. Hence in the earlier stage of identifying the coincident series, we use the CF filter. Once the coincident series are identified, we proceed to use the state of the art Hamilton approach to extract the cyclical component. These cyclical components are the inputs in the construction of the coincident indicator.

7 Conclusion

An important concern for policy-makers is to determine the state of the economy in a timely and reliable manner. Traditionally, GDP growth is considered the state of the economy. However, the GDP series is published with a substantial lag.

Even if GDP is well-measured, it is well acknowledged that no single measure of economic activity can present the true state of the economy (Klein and Moore, 1985). All economic statistics are subject to error, and hence a consensus among several measures is the best path to understanding the state of the economy. In a setting like India or China, there are concerns about GDP measurement. This serves as an additional motivation in favour of constructing a coincident indicator of economic activity.

This paper proposes a quarterly index of business cycle conditions for the Indian economy using the growth cycle approach. Our work improves on the existing literature on the construction of coincident indicators in four ways:

1. It shifts from annual to quarterly analysis,
2. it focuses on a large number of well-measured series including firm-level and project-level data.
3. It applies mainstream statistical procedures for seasonal adjustment and two methods for identification of candidate series.

4. During the aggregation stage, it replaces standard deviation with IQR: a robust measure of volatility to reduce the influence of outliers.

A Cross-correlation

Table 4 shows the cross-correlations of all the candidate series against the cyclical component of net sales.

B Index of concordance

Table 5 shows the Harding-Pagan index of concordance and correlation between state variables.

C Hamilton filter

Hamilton (2017) defines the cyclical component of a trending series as how different is the value at date $t+h$ from the value that we would have expected to see based on its behaviour though date t. This definition has several attractive features. First, the forecast error is stationary for a wide class of non-stationary processes. Second, cyclical factors such as whether a recession occurs over the next two years and the timing of recovery from any downturn prevents us from predicting most of the macro and financial variables at a horizon of 8 quarters.

He further states that a linear projection of y_{t+h} on a constant and the 4 most recent values of y as of date t provides a reasonable way to remove an unknown trend for a broad class of underlying process provided that fourth differences of y_t are stationary. In other words if we fit the following OLS regressions:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h}$$

then the residuals,

Table 4 Cross-correlation with cyclical component of net sales

This table shows the cross-correlation of cyclical components of candidate series with the cyclical component of net sales index. The correlations are shown at contemporaneous period and at leads and lags of upto 5 quarters.

	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5
Exports	-0.21	0.03	0.31	0.57	0.75	0.80	0.68	0.47	0.20	-0.07	-0.30
Cars and Vans Production	0.29	0.41	0.48	0.46	0.36	0.18	-0.07	-0.33	-0.53	-0.66	-0.69
Cars and Vans Sales	0.38	0.46	0.47	0.41	0.28	0.10	-0.16	-0.40	-0.58	-0.68	-0.68
Engineering goods imports	-0.53	-0.33	-0.04	0.29	0.60	0.83	0.88	0.81	0.64	0.40	0.14
Imports	-0.34	-0.12	0.15	0.44	0.67	0.79	0.75	0.60	0.38	0.14	-0.10
Non-oil imports	-0.41	-0.22	0.05	0.35	0.62	0.80	0.80	0.67	0.43	0.14	-0.13
Gold imports	0.04	0.10	0.16	0.23	0.30	0.34	0.31	0.18	-0.03	-0.25	-0.42
Oil imports	-0.16	0.03	0.24	0.43	0.55	0.58	0.49	0.36	0.21	0.07	-0.05
Public issues	0.31	0.30	0.25	0.15	0.01	-0.16	-0.35	-0.45	-0.43	-0.31	-0.13
Public issues: Equity	0.33	0.45	0.48	0.41	0.26	0.05	-0.18	-0.35	-0.44	-0.43	-0.35
Public issues: Debt	-0.02	-0.27	-0.45	-0.56	-0.60	-0.59	-0.54	-0.41	-0.22	0.03	0.29
Non-oil Non-gold imports	-0.50	-0.29	0.00	0.33	0.62	0.82	0.83	0.72	0.51	0.25	-0.01
Govt. Mfg. Ann.	-0.13	0.12	0.36	0.56	0.70	0.75	0.61	0.38	0.11	-0.15	-0.35
Pvt. Mfg. Ann.	0.00	0.11	0.26	0.41	0.55	0.60	0.46	0.25	0.00	-0.22	-0.37
Govt. Infra. Ann.	-0.14	-0.00	0.16	0.34	0.51	0.64	0.57	0.43	0.25	0.06	-0.10
Pvt. Infra. Ann.	-0.22	-0.09	0.06	0.25	0.45	0.62	0.60	0.51	0.36	0.18	0.00
Gvt. Ann.	-0.20	0.02	0.24	0.46	0.63	0.74	0.66	0.49	0.27	0.03	-0.18
Pvt. Ann.	-0.12	0.05	0.24	0.45	0.65	0.79	0.70	0.52	0.29	0.05	-0.15
Govt. Mfg. UI	-0.05	-0.24	-0.40	-0.55	-0.68	-0.76	-0.71	-0.55	-0.30	-0.01	0.25
Pvt. Mfg. UI	-0.31	-0.10	0.13	0.38	0.63	0.83	0.84	0.74	0.55	0.31	0.07
Govt. Infra. UI	0.05	0.05	0.09	0.18	0.29	0.36	0.20	0.05	-0.05	-0.07	-0.03
Pvt. Infra UI	-0.40	-0.20	0.00	0.20	0.38	0.54	0.58	0.55	0.45	0.31	0.16
All India UI	-0.50	-0.33	-0.11	0.15	0.41	0.64	0.68	0.65	0.55	0.41	0.26
Infra UI	-0.33	-0.15	0.04	0.25	0.45	0.60	0.54	0.42	0.29	0.17	0.08
Completed projects	-0.08	-0.08	-0.07	-0.05	-0.01	0.07	0.09	0.13	0.19	0.24	0.25
New projects	0.12	0.19	0.24	0.27	0.25	0.19	0.04	-0.12	-0.27	-0.37	-0.40
Non-infra Pvt. Ann.	-0.05	0.15	0.37	0.59	0.78	0.89	0.75	0.52	0.24	-0.03	-0.25
Non-food credit	-0.19	-0.01	0.22	0.46	0.69	0.84	0.73	0.56	0.35	0.16	0.00
SCB deposits	-0.48	-0.35	-0.18	0.03	0.26	0.49	0.54	0.54	0.50	0.44	0.36
Net sales	-0.23	0.03	0.33	0.63	0.87	1.00	0.87	0.63	0.33	0.03	-0.23
Total expenses	-0.31	-0.07	0.24	0.55	0.82	0.99	0.91	0.70	0.42	0.12	-0.15
Operating profit	0.22	0.47	0.66	0.75	0.74	0.63	0.36	0.08	-0.16	-0.33	-0.41
PAT to sales	0.40	0.56	0.61	0.54	0.37	0.12	-0.15	-0.37	-0.49	-0.51	-0.44
PBDIT to sales	0.43	0.54	0.55	0.43	0.23	-0.01	-0.25	-0.41	-0.47	-0.43	-0.32
INR USD	0.10	-0.17	-0.42	-0.59	-0.65	-0.59	-0.45	-0.24	0.01	0.25	0.46
FDI	-0.36	-0.18	0.05	0.33	0.61	0.85	0.89	0.82	0.64	0.38	0.09
M1	-0.10	-0.01	0.09	0.17	0.24	0.26	0.15	0.05	-0.02	-0.05	-0.04
Reserve Money	-0.05	-0.26	-0.47	-0.62	-0.66	-0.57	-0.35	-0.07	0.21	0.43	0.56
COSPI PE	0.39	0.54	0.61	0.57	0.40	0.15	-0.16	-0.41	-0.56	-0.60	-0.55
COSPI Closing	0.26	0.48	0.61	0.64	0.54	0.34	0.05	-0.21	-0.39	-0.48	-0.49
World trade	0.02	0.30	0.56	0.77	0.87	0.82	0.60	0.30	-0.01	-0.29	-0.50
World IIP	-0.06	0.23	0.52	0.75	0.86	0.85	0.66	0.39	0.10	-0.17	-0.40
REER	0.08	0.27	0.42	0.50	0.49	0.38	0.20	-0.02	-0.25	-0.45	-0.59
Rubber production	0.05	0.09	0.12	0.13	0.10	0.03	-0.08	-0.19	-0.26	-0.30	-0.31
Tyre production	0.30	0.44	0.54	0.55	0.45	0.25	-0.04	-0.34	-0.58	-0.73	-0.76
Coal production	-0.28	-0.39	-0.46	-0.48	-0.45	-0.36	-0.25	-0.09	0.11	0.32	0.51
Tax revenue	0.26	0.41	0.56	0.67	0.68	0.58	0.31	0.05	-0.15	-0.27	-0.34
Capital issuance	0.24	0.23	0.20	0.14	0.06	-0.05	-0.23	-0.34	-0.35	-0.26	-0.10
Air traffic	0.27	0.42	0.50	0.49	0.38	0.18	-0.10	-0.37	-0.58	-0.69	-0.69
Foreign tourist arrivals	-0.01	0.29	0.57	0.79	0.90	0.88	0.66	0.37	0.07	-0.21	-0.43
Acrylic fibre production	-0.11	-0.26	-0.43	-0.57	-0.65	-0.63	-0.45	-0.21	0.04	0.24	0.39
Commercial vehicles production	0.37	0.54	0.64	0.66	0.57	0.39	0.14	-0.12	-0.35	-0.53	-0.65
Steel production	0.25	0.49	0.68	0.79	0.78	0.64	0.33	-0.03	-0.35	-0.58	-0.70
HCV production	0.30	0.47	0.59	0.61	0.53	0.36	0.12	-0.14	-0.37	-0.55	-0.66
LCV production	0.25	0.34	0.39	0.42	0.41	0.38	0.27	0.13	-0.02	-0.17	-0.32
Nylon filament yarn production	0.12	0.04	-0.05	-0.14	-0.24	-0.35	-0.44	-0.50	-0.51	-0.46	-0.34
Pig iron production	0.07	0.03	0.00	-0.01	-0.01	0.00	-0.05	-0.07	-0.04	0.03	0.13
Refined copper production	0.21	0.31	0.38	0.42	0.44	0.47	0.37	0.26	0.13	0.01	-0.10
Sugar production	0.14	0.39	0.62	0.79	0.86	0.82	0.62	0.36	0.07	-0.22	-0.48
Tea production	0.24	0.26	0.25	0.23	0.20	0.16	0.06	-0.07	-0.20	-0.32	-0.39
Three wheelers production	0.58	0.64	0.63	0.56	0.42	0.21	-0.08	-0.38	-0.64	-0.80	-0.84
Trucks production	0.34	0.50	0.60	0.61	0.52	0.34	0.08	-0.18	-0.40	-0.58	-0.68
Two wheelers production	0.50	0.48	0.41	0.30	0.13	-0.08	-0.33	-0.55	-0.68	-0.72	-0.67
Commercial vehicles sales	0.30	0.41	0.50	0.54	0.53	0.44	0.25	0.03	-0.18	-0.37	-0.52
HCV sales	0.35	0.51	0.60	0.60	0.51	0.33	0.07	-0.19	-0.41	-0.57	-0.67
LCV sales	0.25	0.36	0.44	0.48	0.48	0.44	0.30	0.14	-0.03	-0.18	-0.32
Electricity generation	-0.11	0.02	0.14	0.25	0.34	0.42	0.39	0.33	0.23	0.10	-0.06
Electricity requirement	-0.29	-0.18	-0.04	0.12	0.30	0.48	0.54	0.56	0.55	0.49	0.37
Port traffic	-0.29	-0.07	0.14	0.31	0.43	0.48	0.40	0.27	0.12	-0.02	-0.13
Agriculture trade balance	-0.24	-0.02	0.23	0.48	0.66	0.75	0.72	0.60	0.41	0.19	-0.06
Petroleum consumption	-0.29	-0.24	-0.16	-0.05	0.08	0.22	0.31	0.38	0.43	0.44	0.38

Table 5 Harding-Pagan Index of Concordance and correlation between state variables

This table shows the Harding-Pagan Index of Concordance. The Index of Concordance (IOC) shows the proportion of times the cyclical component of the reference series (net sales index) and the candidate series are in the same phase i.e. in recession or in expansion. We use the Bry and Boschan (1971) turning points algorithm to identify phases of expansion and recession. We report the correlation between the state variables of the candidate and the reference series ($\hat{\rho_{xy}}$). We also report p-values for the Heteroskedasticity-Autocorrelation (HAC) corrected t-statistics for $\hat{\rho_{xy}}$.

Variable	IOC	Correlation	HP-tstat	HP-pvalue
Exports	0.87	0.74	5.60	0.00
Cars and Vans Production	0.70	0.39	2.17	0.04
Cars and Vans Sales	0.66	0.30	1.59	0.12
Engineering goods imports	0.83	0.65	4.66	0.00
Imports	0.81	0.61	3.87	0.00
Non-oil imports	0.81	0.61	4.95	0.00
Gold imports	0.57	0.18	1.15	0.26
Oil imports	0.72	0.43	2.58	0.01
Public issues	0.49	-0.01	-0.03	0.98
Public issues: Equity	0.53	0.02	0.10	0.92
Public issues: Debt	0.45	-0.12	-0.58	0.57
Non-oil Non-gold imports	0.83	0.66	5.43	0.00
Govt. Mfg. Ann.	0.74	0.49	2.73	0.01
Pvt. Mfg. Ann.	0.64	0.27	1.39	0.17
Govt. Infra. Ann.	0.77	0.52	2.90	0.01
Pvt. Infra. Ann.	0.72	0.44	2.59	0.01
Gvt. Ann.	0.83	0.65	5.60	0.00
Pvt. Ann.	0.70	0.39	2.07	0.04
Govt. Mfg. UI	0.47	-0.13	-0.63	0.53
Pvt. Mfg. UI	0.68	0.34	2.03	0.05
Govt. Infra. UI	0.55	0.09	0.49	0.62
Pvt. Infra UI	0.51	0.04	0.22	0.83
All India UI	0.72	0.43	3.13	0.00
Infra UI	0.64	0.25	1.29	0.20
Completed projects	0.55	0.06	0.29	0.77
Non-infra Pvt. Ann.	0.66	0.30	1.59	0.12
Non-food credit	0.64	0.25	1.72	0.09
SCB deposits	0.72	0.43	2.73	0.01
Total expenses	0.96	0.91	15.37	0.00
Operating profit	0.62	0.22	1.43	0.16
PAT to sales	0.60	0.17	1.10	0.28
PBDIT to sales	0.36	-0.27	-1.43	0.16
INR USD	0.32	-0.41	-2.67	0.01
FDI	0.87	0.74	6.48	0.00
M1	0.72	0.43	2.19	0.03
Reserve Money	0.26	-0.49	-3.30	0.00
COSPI PE	0.70	0.38	2.12	0.04
COSPI Closing	0.70	0.39	2.35	0.02
World trade	0.83	0.65	5.18	0.00
World IIP	0.85	0.69	6.39	0.00
REER	0.62	0.27	1.53	0.13
Rubber production	0.70	0.39	2.15	0.04
Tyre production	0.81	0.61	4.46	0.00
Coal production	0.53	0.03	0.11	0.91
Tax revenue	0.57	0.15	0.74	0.46
Capital issuance	0.53	0.07	0.38	0.70
Air traffic	0.79	0.56	3.87	0.00
Foreign tourist arrivals	0.79	0.56	4.06	0.00
Acrylic fibre production	0.30	-0.40	-2.15	0.04
Commercial vehicles production	0.68	0.33	1.81	0.08
Steel production	0.72	0.43	2.76	0.01
HCV production	0.68	0.33	2.34	0.02
LCV production	0.62	0.21	1.10	0.28
Nylon filament yarn production	0.51	-0.04	-0.16	0.87
Pig iron production	0.45	-0.16	-0.93	0.35
Refined copper production	0.51	0.01	0.03	0.97
Sugar production	0.81	0.61	3.72	0.00
Tea production	0.57	0.13	0.61	0.54
Three wheelers production	0.66	0.30	1.57	0.12
Trucks production	0.68	0.33	2.34	0.02
Two wheelers production	0.64	0.26	1.11	0.27
Commercial vehicles sales	0.64	0.25	1.35	0.18
HCV sales	0.66	0.29	1.64	0.11
LCV sales	0.57	0.12	0.60	0.55
Electricity generation	0.64	0.24	1.35	0.18
Electricity requirement	0.66	0.29	1.59	0.12
Port traffic	0.66	0.36	2.22	0.03
Agriculture trade balance	0.72	0.43	2.38	0.02
Petroleum consumption	0.66	0.30	1.39	0.17

$$\hat{v}_{t+h} = y_{t+h} - \hat{\beta}_0 - \hat{\beta}_1 y_t - \hat{\beta}_2 y_{t-1} - \hat{\beta}_3 y_{t-2} - \hat{\beta}_4 y_{t-3}$$

are the cyclical component of the series.

D Christiano-Fitzgerald filter

Cycle extraction is a crucial step in the growth cycle approach. The class of band-pass filters translate the series in a frequency domain framework. In the frequency domain, we can treat the series as a construction of sine waves of different wave length. The trend part of the series is comprised by the low frequency (high wave length) sine waves, whereas the noise is formed by a set of high frequency sine waves (OECD, 2016).

Once we have the series in the frequency domain, we can single out the cycles we are interested in, and eliminate the components whose wave length is too long (trend) or too short (noise). The category of band-pass filters help in extracting cycles of a chosen frequency (Christiano and Fitzgerald, 2003; Baxter and King, 1999). The de-trending methods need to be aligned with the chosen business cycle frequency or periodicity.

The cyclical component in Christiano-Fitzgerald filter is calculated as follows:

$c_t = B_0 y_t + B_1 y_{t+1} + ... + B_{T-1-t} y_{T-1} + B^{\sim}_{T-t} y_T + B_1 y_{t-1} + ... + B_{t-2} y_2 + B^{\sim}_{t-1} y_1$

where $B_j = \frac{sin(jb)-sin(ja)}{\pi j}$, $j \geq 1$, and $B_0 = \frac{b-a}{\pi}$, $a = \frac{2\pi}{p_u}$, $b = \frac{2\pi}{p_l}$

$$\tilde{B}_k = -\frac{1}{2}B_0 - \sum\nolimits_{i=1}^{k-1} B_j$$

Where the parameters p_u and p_l are the cut-off cycle length and c_t is the cyclical component.

E Detection of turning points

The Bry-Boschan (BB) and Harding Pagan (HP) algorithms find the turning points as follows:

- The data is smoothed after outlier adjustment by constructing short-term moving averages.
- The preliminary set of turning points are selected for the smoothed series subject to the criterion described later.
- In the next stage, turning points in the raw series is identified taking results from smoothed series as the reference.

The identification of turning point dates is done subject to the following rules:

- The first rule states that the peaks and troughs must alternate.
- The second step involves the identification of local minima (troughs) and local maxima (peaks) in a single time series, or in y_t after a log transformation.
- Peaks are found where y_s is larger than k values of y_t in both directions.
- Troughs are identified where y_s is smaller than k values of y_t in both the directions.
- Bry and Boschan (1971) suggested the value of k as 5 for monthly frequency which Harding and Pagan (2002) transformed to 2 for quarterly series.
- Censoring rules are put in place for minimum duration of phase (from peak to trough or trough to peak) and for a complete cycle (from peak to peak or from trough to trough).
- Harding and Pagan identify minimum duration of a phase to be 2 quarters and the minimum duration of a complete cycle to be 5 quarters.

- For monthly data, the minimum duration is 5 months and 15 months for phase and cycle respectively.
- The identification of turning points is avoided at extreme points.

F List of variables

This table shows the list of variables considered for identification of coincident series.

Variables	Source
Merchandise exports	Ministry of Trade & Commerce
Cars and Vans Production	Society of Indian Automobile Manufacturers (SIAM)
Cars and Vans Sales	SIAM
Engineering goods imports	Ministry of Trade & Commerce
Imports	Ministry of Trade & Commerce
Non-oil imports	Ministry of Trade & Commerce
Gold imports	Ministry of Trade & Commerce
Oil imports	Ministry of Trade & Commerce
Public issues	SEBI
Public issues: Equity	SEBI
Public issues: Debt	SEBI
Non-oil Non-gold imports	Ministry of Trade & Commerce
Govt. Mfg. Announced	CMIE Capex
Pvt. Mfg. Announced	CMIE Capex
Govt. Infra. Announced	CMIE Capex
Pvt. Infra. Announced	CMIE Capex
Gvt. Announced	CMIE Capex
Pvt. Announced	CMIE Capex
Govt. Mfg. Under Implementatation	CMIE Capex
Pvt. Mfg. Under Implementatation	CMIE Capex
Govt. Infra. Under Implementatation	CMIE Capex
Pvt. Infra Under Implementatation	CMIE Capex
All India Under Implementatation	CMIE Capex
Infra Under Implementatation	CMIE Capex
Completed projects	CMIE Capex
New projects	CMIE Capex
Non-infra Pvt. Announced	CMIE Capex
Non-food credit	RBI
SCB deposits	RBI
Net sales	CMIE Prowess
Total expenses	CMIE Prowess
Operating profit	CMIE Prowess
Export income	CMIE Prowess
PAT to sales	CMIE Prowess
PBDIT to sales	CMIE Prowess
INR USD	RBI

Table 6 List of variables

Variable	Source
FDI	DIPP, Ministry of Commerce
M1	RBI
Reserve Money	RBI
COSPI PE	CMIE EO
COSPI Closing	CMIE EO
World trade	CPB Netherlands Bureau for Economic Policy Analysis
World IIP	CPB Netherlands Bureau for Economic Policy Analysis
REER	BIS
Rubber production	CMIE IAS
Tyre production	CMIE IAS
Coal production	CMIE IAS
Tax revenue	Ministry of Finance
Capital issuance	CMIE EO
Air traffic	CMIE EO
Foreign tourist arrivals	CMIE EO
Acrylic fibre production	CMIE IAS
Commercial vehicles production	SIAM
Steel production	CMIE IAS
HCV production	SIAM
LCV production	SIAM
Nylon filament yarn production	CMIE IAS
Pig iron production	CMIE IAS
Refined copper production	CMIE IAS
Sugar production	CMIE IAS
Tea production	CMIE IAS
Three wheelers production	SIAM
Trucks production	SIAM
Two wheelers production	SIAM
Commercial vehicles sales	SIAM
HCV sales	SIAM
LCV sales	SIAM
Electricity generation	Central Electricity Authority
Electricity requirement	Central Electricity Authority
Port traffic	CMIE EO
Agriculture trade balance	CMIE EO
Credit-Deposit ratio	RBI

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Radhika Pandey, is Fellow, NIPFP
Email: radhika.pandey@nipfp.org.in

Ila Patnaik, is Professor, NIPFP
Email: ila.patnaik@nipfp.org.in

Ajay Shah, is Professor, NIPFP
Email: ajay.shah@nipfp.org.in

National Institute of Public Finance and Policy,
18/2, Satsang Vihar Marg,
Special Institutional Area (Near JNU),
New Delhi 110067
Tel. No. 26569303, 26569780, 26569784
Fax: 91-11-26852548
www.nipfp.org.in