Reserve Bank of India Occasional Papers
Vol. 31. No.2. Monsoon 2010

Macroeconomic Forecasting using Dynamic Factor Models

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During the recent period, dynamic factor modelling is gaining importance as one of the key forecasting tools exploiting the information contained in large datasets. The major advantage with the factor modelling approach is that, it can cope with many variables without running into scarce degrees of freedom that often arise in regression analysis. This technique allows forecasters to summarize the information contained in large datasets and extract a few common factors from them. This study attempts to develop a dynamic factor model (DFM) to forecast industrial production and price level in India. For this purpose, domestic as well as external economic indicators, that appear to contain information about the movement of industrial production/ price level, were used. Based on empirical analysis, it is found that the out-of-sample forecast accuracy of DFM, as measured by root mean square percentage error, is better than the OLS regression.

JEL Classification : C3, E2, E3.
Keywords : Dynamic Factor Model, Forecast, Inflation, Output

Introduction

Reliable forecast of key macro economic indicators plays an important role for the formulation of monetary and fiscal policies of a country. Academic work on macroeconomic modeling and economic forecasting historically has focused on models with only a handful of variables. In contrast, economists in business and government, whose

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job is to track the swings of the economy and to make forecasts that inform decision-makers in real time, have long examined a large number of variables. Practitioners use many series when making their forecasts, and despite the lack of academic guidance about how to proceed, they suggest that these series have information content beyond that contained in the major macroeconomic aggregates. But if so, what are the best ways to extract this information and to use it for real-time forecasting? In the same line, Stock and Watson (2006) had focused on the case of United States, where, literally thousands of potentially relevant time series were available on a monthly or quarterly basis.

During the recent period, one of the key forecasting tools, which is gaining importance for dealing with large datasets, is dynamic factor modelling. The major advantage with the factor modelling approach is that, it can cope with many variables without running into scarce degrees of freedom that often arise in regression analysis. Besides this, by using factor models, the idiosyncratic movements, which possibly include measurement error and local shocks, can be eliminated. Through factor analysis, one can extract the unobserved factors that are common to the economic variables and these can be used for real time dynamic forecasting. For instance, Stock and Watson (1989) used a single factor to model the co-movements of four main macroeconomic aggregates. DFM plays an important role in the theory of Capital Asset Pricing Model (CAPM) also, as asset returns are often modeled as a function of market risk, where market risk is a common factor explaining the returns of many assets. Similarly in Arbitrage Pricing Theory (APT), returns are considered as function of other indicators like market return, inflation risk, liquidity risk etc as well as of some idiosyncratic component. This gives a more reliable signal for policy makers and prevents them from reacting to idiosyncratic movements. The uses of dynamic factor models have been improved by recent advances in estimation techniques [Stock and Watson (2002); Forni, Hallin, Lippi and Reichlin (2005) and Kapetanios and Marcellino (2004)].

These techniques allow forecasters to summarize the information contained in large datasets and extract a few common factors from them. All or a subset of the estimated factors are then entered into simple regression models to forecast the economic indicators.

The co-movement of contemporaneous economic variables may be due to the fact that they are driven in part by common shocks. This allows parsimonious modeling while corresponding to the notion of binding macroeconomic comovement. To overcome the problem of degrees of freedom for estimation of an economic system, reduction of dimensions has gained importance in the recent period. Factor analysis allows for dimension reduction and has become a standard econometric tool for both measuring comovement and forecasting macroeconomic variables.

The primary objective of the study is to forecast the inflation and output growth using dynamic factor models. The complete list of indicators that have been considered for empirical analysis is provided in the Annexure. The indicators cover the various sectors of the economy, *viz.,* monetary and banking, financial, price, real and external. Also the performance of the dynamic factor model has been compared with alternative methods like the time series and econometric techniques.

The remainder of the study is divided into three sections. Section I describes briefly the methodology of Dynamic Factor Model (DFM). The empirical results related to DFM and assessment of the forecast performance are discussed in Section II. Finally, Section III concludes.

Section I
Methodology of the Dynamic Factor Model

Factor models have a long history of use in cross-sectional settings, and their generalization to dynamic environments is due to Sargent and Christopher (1977), Geweke (1977) and Watson and Engle (1983). Important recent contributions include Stock and Watson (1989, 1991, 1993) and Quah and Sargent (1993), among others. The dynamic factor model of Stock and Watson (1991) was developed as a modern statistical framework for computing a composite index of coincident indicators.

Given a data set, one can divide it into a common part, which captures the comovements of the cross section and a variable specific idiosyncratic part. A vector of *N* variables is represented as the sum of two unobservable orthogonal components, *viz.* a common component, driven by few (fewer than N) common factors, and an idiosyncratic component, driven by N idiosyncratic factors. If we have only one common factor, affecting only contemporaneously all of the variables, such a factor can be interpreted as the reference cycle (Stock and Watson, 1989). These models imply that the economic activity is driven by some few latent-driving forces, which can be revealed by the estimation of the dynamic factors. However, it may be noted that the factors, their loadings, as well as the idiosyncratic errors are not observable.

In one-factor model, movements in the N macroeconomic variables of interest, $\underset{\sim}{X}_t$, are determined by changes in the unobserved common factor, $\underset{\sim}{F}_t$ and by the N-dimensional idiosyncratic component, $\underset{\sim}{e}_t$:

Let x_{it} be the observed data for the i[th] cross-section unit at time t, for i = 1, . . . ,N, and t = 1, . . ,T. Consider the following model:

$$x_{it} = \underset{\sim}{\lambda}_i^{\prime} \underset{\sim}{F}_t + e_{it} \qquad \text{...(1)}$$

where $\underset{\sim}{F}_t$ is a vector of common factors, $\underset{\sim}{\lambda}_i$ is a vector of factor loadings associated with $\underset{\sim}{F}_t$, and e_{it}, is the idiosyncratic component of x_{it}. The product $\underset{\sim}{\lambda}_i^{\prime} \underset{\sim}{F}_t$ is called the common component of x_{it}. Equation (1) is then the factor representation of the data.

Consider the forecasting equation for a scalar series,

$$y_{t+1} = \underset{\sim}{a}^{\prime} \underset{\sim}{F}_t + \underset{\sim}{b}^{\prime} \underset{\sim}{W}_t + e_t$$

Where the set of variables $\underset{\sim}{W}_t$, are observable. Although $\underset{\sim}{F}_t$ is not observable, we observe x_{it} , i = 1,. . . ,N. Suppose x_{it}, bears relation with ***F,*** as defined in (1), then (1) can be interpreted as the reduced-form representation of X_i, in terms of the unobservable factors. Let us denote the estimate of $\underset{\sim}{F}_t$ by $\hat{\underset{\sim}{F}}_t$. Then one can regress y_t on $\hat{\underset{\sim}{F}}_{t-1}$, and $\underset{\sim}{W}_{t-1}$ to obtain the coefficients $\hat{a}$ and $\hat{b}$ from which a forecast can be generated. Stock and Watson (1998, 1999) showed that this approach of forecasting outperforms many competing forecasting methods.

Alternatively, in the frequency domain, the dynamics among a number of important economic variables can be characterized by high pairwise coherences at the lower business cycle frequencies. Dynamics in frequency domain can be observed through cross spectral density function, which presents the same dynamic information. The cross spectral density matrix decomposes variation and covariation among variables by frequency, permitting one to concentrate on the dynamics of interest (e.g. the business-cycle dynamics correspond to periods of roughly 2-8 years). Transformations of both the real and imaginary parts of the spectral density matrix have immediate interpretation in business-cycle analysis - the *coherence statistic* between any two economic variables effectively presents the strength of their relationship at different frequencies, while the *phase statistic* presents the lead/lag relationships at different frequencies.

However, a factor model must have two characteristics. First, it must be dynamic to capture the structural changes in the economy. Secondly, it must allow for cross-correlation among idiosyncratic components, since orthogonality is an unrealistic assumption for most applications. The model we propose to use in this project has both the characteristics. It encompasses as a special case of the static ‘approximate factor model’ of Chamberlain (1983) and Chamberlain and Rothschild (1983), which allows for correlated idiosyncratic components. It also generalizes the factor model of Sargent and Sims (1977) and Geweke (1977), which is dynamic in nature, but has orthogonal idiosyncratic components. An important feature of this model is that the common component is allowed to have an infinite Moving Average (MA) representation, so as to accommodate for both autoregressive (AR) and MA responses to common factors. In this respect, it is more general than a static factor model where lagged factors are introduced as additional static factors, since in such model AR responses are ruled out.

Analysis of co-movement in dynamic settings typically makes use of two nonparametric tools, *viz.,* the autocorrelation function and the spectral density function. In the time domain, one examines multivariate dynamics through the autocorrelation function, which estimates the correlations of each variable with its own past as well as with the past of other economic variables in the system. As an example, one can characterize the dynamics of output, consumption, investment, net exports, money and prices across different countries over the years.

The basic difference between the classical factor analysis and dynamic factor analysis is that, in the former, the factors are identified by multiplying by a nonsingular $(r \times r)$ matrix, whereas, in the later, the factors are identified by multiplying by a nonsingular $(r \times r)$ matrix lag polynomial. The theory of dynamic factor model is that the covariation among a set of economic variables at leads and lag can be traced to a few underlying unobserved factors. DFMs express observed variables in terms of distributed lag of a small number of unobserved common factors, plus idiosyncratic disturbance, which may be serially correlated:

$$Y_{it} = \lambda_i(L)F_t + u_{it}, i = 1,2,---,n$$

where F_t is an $(r \times 1)$ vector of unobserved factors, $\lambda_i(L)$ is a $(r \times 1)$ vector lag polynomial, known as the *dynamic factor loadings* and u_{it} is the idiosyncratic disturbance. The factors and idiosyncratic disturbance are assumed to be uncorrelated at various leads and lags, *i.e.,*

$$E(F_t u_{is}) = 0 \text{ for all } i, s$$

The unobserved factors are modeled as a linear dynamic process,

$$\Gamma(L)F_t = \eta_t$$

where $\Gamma(L)$ is a matrix lag polynomial and η_t is a $(r \times 1)$ disturbance vector.

Consider a single forecasting equation for Y_t, so that,

$$Y_t = \lambda_Y(L)F_t + u_{Yt}$$

where $\{u_{Yt}\}$ is distributed independently of $\{F_t\}$. Further, assume that $\{u_{Yt}\}$ follows the autoregressive process,

$$\Delta_Y(L)u_{Yt} = v_{Yt}$$

Then,

$$\Delta_Y(L)Y_{t+1} = \Delta_Y(L)\lambda_Y(L)F_{t+1} + \Delta_Y(L)u_{Y,t+1}$$
$$\Rightarrow Y_{t+1} = \Delta_Y(L)\lambda_Y(L)F_{t+1} + \gamma(L)Y_t + v_{t+1}$$

where $\gamma(L) = L^{-1}(1-\Delta_Y(L))$

Thus,

$$E[Y_{t+1}/Y_t, F_t, Y_{t-1}, F_{t-1}, ---] = E[\Delta_Y(L)\lambda_Y(L)F_{t+1} + \gamma(L)Y_t + v_{t+1}/Y_t, F_t, Y_{t-1}, F_{t-1}, ---]$$
$$= \beta(L)F_t + \gamma(L)Y_t$$

where $\beta(L)F_t = E[\Delta_Y(L)\lambda_Y(L)F_{t+1}/F_t, F_{t-1}, ---]$

Setting, $Z_t = Y_t$, we have,

$$Y_{t+1} = \beta(L)F_t + \gamma(L)Z_t + \varepsilon_{t+1}$$
$$\textit{where } \varepsilon_{t+1} = v_{t+1} + [\Delta_Y(L)\lambda_Y(L)F_{t+1} - \beta(L)F_t]$$
$$= v_{t+1} + [\Delta_Y(L)\lambda_Y(L)F_{t+1} - E[\Delta_Y(L)\lambda_Y(L)F_{t+1}/F_t, F_{t-1}, ---]]$$

has conditional mean zero given F_t, Y_t and their lags. The notation Z_t generalizes the equation so that observable predictors other than lagged Y_t can be included in the regression. As an illustration, Z_t may incorporate an observable variable that may be valuable to forecast Y_{t+1} even after its inclusion of the factors and lags of the dependent variable.

The parameters of the DFM can be estimated by maximum likelihood using the Kalman filter and the dynamic factors can be estimated using the Kalman smoother [Stock and Watson (1989, 1991)].

h-step ahead forecast:

Multi-step ahead forecast can be estimated based on two alternative ways – the iterated or the direct method. The iterated h-step ahead forecast is computed by solving the full DFM forward through the Kalman filter. On the other hand, the h-step ahead forecast, by the direct method, is done by projecting Y_{t+h}^{h} onto the estimated factors and observables, *i.e.,* by estimating $\beta_h(L)$ and $\gamma_h(L)$ in the equation,

$$Y_{t+h}^{h} = \beta_h(L)F_{t/t} + \gamma_h(L)Z_t + \varepsilon_{t+h}^{h}$$

utilizing data through the period (t-h). Consistent estimates of $\beta_h(L)$ and $\gamma_h(L)$ can be obtained by OLS as the signal extraction error $(F_{t-i} - F_{t-i/t})$ is uncorrelated with $F_{t-j/t}$ and Y_{t-j} for $j \geq 0$. The forecast for period $T + h$ is then $\hat{\beta}_h(L)F_{t/t} + \hat{\gamma}_h(L)Z_t$.

Section II
Empirical Estimates

The study uses monthly data covering the period from April 1994 to March 2008 consisting 168 sample points. The list of variables with description and sources are provided in the Annexure. To test the forecasting performance of the alternative methods, the whole sample period is divided into two sub-samples, *viz.,* in-sample and out-of-sample. The in-sample, covering the period from April 1994 to March 2007, is used to estimate the parameters, while the last twelve points from April 2007 to March 2008, were used to test for the out-of-sample forecasting performance.

2.1. Model for Industrial Production

2.1.1. Estimates of the model

For developing a dynamic factor model to forecast the monthly industrial production in India, thirteen economic indicators were selected. The estimates cover the sample from April 1994 to March 2007. Table-1 presents the list of selected indicators.

Table 1: List of economic indicators selected to forecast IIP

Indicator Name	Abbreviation
Cargo Handled at Major Ports	CARGO
Production of Cement	CEMENT
Production of Commercial Motor Vehicles	CMV
Demand Deposits	DD
Euro Area IIP	EURO_IIP
Exports	EXPORT
IIP Capital Goods	IIP_CAP
Non-Food Credit	NFC
Non-Oil Imports	NONOIL
Rs. Dollar Exchange Rate	RSDOLLAR
Steel Production	STEEL
USA IIP	US_IIP
WPI Manufactured Products	WPIMAN

Based on these selected thirteen indicators, factor analysis has been performed and obtained thirteen factors. Table-2 presents the estimates of the initial eigen values along with the percentage of total variance explained corresponding to these eigen values. For determining the number of factors that to be retained for further analysis, we have applied the rule based on eigen values-greater-than-one. The factors with eigen values greater than 1.0 are considered significant, explaining an important amount of the variability in the data, while eigen values less than 1.0 are considered too weak, not explaining a significant portion of the data variability. Based on this rule, the first six eigen values were selected, which together explained 62.7 percent of the total variation. The selected first six factors were than rotated through the application of Varimax method. The Component Score Coefficient Matrix is presented in Table-3.

Table 2: Factors Extraction – Industrial Production

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.0	15.1	15.1	2.0	15.1	15.1	1.7	12.9	12.9
2	1.6	12.0	27.1	1.6	12.0	27.1	1.6	12.4	25.3
3	1.3	9.9	37.0	1.3	9.9	37.0	1.3	10.2	35.5
4	1.2	8.9	45.9	1.2	8.9	45.9	1.2	9.4	44.9
5	1.1	8.5	54.4	1.1	8.5	54.4	1.2	9.1	54.0
6	1.1	8.3	62.7	1.1	8.3	62.7	1.1	8.7	62.7
7	1.0	7.3	70.1						
8	0.8	6.4	76.4						
9	0.8	5.9	82.3						
10	0.8	5.8	88.1						
11	0.6	4.4	92.5						
12	0.6	4.3	96.8						
13	0.4	3.2	100.0						

Table 3: Component Score Coefficient Matrix

	Components					
	Factor-1	Factor-2	Factor-3	Factor-4	Factor-5	Factor-6
CARGO	0.308	0.283	0.211	-0.013	0.192	-0.007
CEMENT	0.178	-0.103	0.066	-0.497	0.027	0.114
CMV	-0.054	0.026	-0.118	0.014	0.682	0.137
DD	-0.095	0.533	0.062	-0.071	-0.079	0.018
EURO_IIP	-0.024	0.106	-0.269	0.130	-0.457	0.255
EXPORT	0.509	-0.107	0.000	-0.079	-0.036	0.111
IIP_CAP	0.185	0.015	-0.193	0.273	0.335	-0.066
NFC	0.011	0.464	0.027	-0.010	0.041	-0.005
NONOIL	0.392	-0.010	-0.065	0.089	-0.098	-0.200
RSDOLLAR	-0.053	0.035	0.556	0.288	-0.038	-0.183
STEEL	0.064	0.086	0.511	-0.089	-0.058	0.180
US_IIP	-0.035	0.011	-0.010	0.053	0.038	0.795
WPIMAN	0.125	-0.150	0.196	0.623	-0.022	0.190

2.1.2. Out-of-sample forecasting

As mentioned earlier, the last twelve data points covering the sample from April 2007 to Mach 2008, has been used to test for the out-of-sample forecasting performance of the model. A comparison has been made between the out-of-sample forecasting performances of the DFM with a simple equation based on the ordinary least square (OLS) regression of the estimated factors. Table-4 presents the forecast errors (measured as percentage of actual industrial production), based on the two alternative methods, along with the Root Mean Square

Table 4: Forecast errors (as percentage of industrial production) of alternative models

Month	DFM	OLS
Apr-07	0.4	3.4
May-07	1.4	2.8
Jun-07	2.0	3.4
Jul-07	3.0	4.0
Aug-07	2.1	3.1
Sep-07	2.9	4.4
Oct-07	2.8	4.0
Nov-07	2.8	4.5
Dec-07	2.2	3.2
Jan-08	2.7	3.7
Feb-08	2.9	4.2
Mar-08	2.7	5.2
RMSPE	2.45	3.87

Table 5: List of economic indicators selected to forecast WPI

Indicator Name	Abbreviation
BSE Sensex	BSE
Food Stock	FOODSTOCK
International Edible Oil Price	IEDIBLE
IIP Manufacturing	IIPMAN
International Metal Price	IMP
Industrial Raw Material Price	INDRM
Narrow Money	M1
Oil Price - Indian Basket	OIL_INDIA
Rs Dollar Exchange Rate	RSDOLLAR

Percent Error (RMSPE). The RMSPE of the DFM is found to be 2.45 percent, which is significantly lower than 3.87 percent based on the OLS regression, indicating better explanatory power of the DFM than the OLS method.

2.2. Model for Price Level / Inflation

2.2.1. Estimates of the model

For developing a dynamic factor model to forecast the monthly inflation in India, nine economic indicators were selected. Table-5 presents the list of selected indicators.

Based on these selected nine indicators, factor analysis has been performed and accordingly nine factors were extracted initially. Table-6 presents the estimates of the initial eigen values along with

Table 6: Factors extraction – WPI

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.9	21.0	21.0	1.9	21.0	21.0	1.6	18.0	18.0
2	1.2	13.6	34.6	1.2	13.6	34.6	1.3	14.9	32.9
3	1.2	13.0	47.6	1.2	13.0	47.6	1.2	13.9	46.8
4	1.1	12.5	60.1	1.1	12.5	60.1	1.2	13.3	60.1
5	0.9	9.8	69.9						
6	0.8	9.4	79.4						
7	0.7	7.6	87.0						
8	0.6	6.9	93.9						
9	0.5	6.1	100.0						

Table 7: Component Score Coefficient Matrix

	Component			
	Factor-1	Factor-2	Factor-3	Factor-4
BSE	-0.46	-0.04	0.06	-0.08
FOODSTOC	0.30	0.02	0.48	0.23
IEDIBLE	-0.11	0.10	0.14	0.66
IIPMAN	0.14	0.63	-0.34	0.06
IMP	-0.17	0.42	0.10	0.18
INDRM	0.09	-0.03	-0.12	0.48
M1	-0.05	-0.05	0.58	-0.06
OILINDIA	0.11	0.43	0.26	-0.26
RSDOLLAR	0.52	0.10	0.12	-0.11

the percentage of total variance explained corresponding to these eigen values. For determining the number of factors to be retained for further analysis, eigen values-greater-than-one rule has been applied as done previously. Based on this rule, the first four eigen values were selected, which together explained 60.1 percent of the total variation. The selected first four factors were than rotated through the application of Varimax method. The Component Score Coefficient Matrix is presented in Table-7.

2.2.2. Out-of-sample forecasting

As done earlier, the out-of-sample forecasting performance of the DFM has been compared with that of a simple OLS regression based on the selected four factors. Table-8 presents the forecast

Table 8: Forecast errors (as percentage of WPI) of alternative models

Month	DFM	OLS
Apr-07	0.1	0.1
May-07	0.6	0.8
Jun-07	1.0	1.3
Jul-07	1.0	1.2
Aug-07	1.1	1.5
Sep-07	1.6	2.0
Oct-07	1.5	1.9
Nov-07	1.2	1.8
Dec-07	0.2	1.0
Jan-08	-0.6	0.3
Feb-08	-0.9	0.1
Mar-08	-2.1	-0.7
RMSPE	1.14	1.24

errors (measured as percentage of actual WPI), based on the two alternative methods, along with the Root Mean Square Percent Error (RMSPE). The RMSPE of the DFM is found to be 1.14 percent which is marginally lower than that of the OLS regression based estimate. This supports the better explanatory power of the DFM than the OLS method.

Section III
Conclusion

This study explores to develop dynamic factor models (DFM) to forecast industrial production and price level in India. For this purpose, economic indicators that contain information about the future movement of industrial production/ price level are selected. These indicators chosen represent both domestic as well as external factors. Based on empirical analysis, it appears that the performances of DFM are quite encouraging. It is found that the out-of-sample forecast accuracy of DFM, as measured by root mean square percentage error, is better than the OLS regression.

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Annexure

List of Indicators for Inflation and Output

Indicator	Source	Definition
Monetary and Banking Indicators		
M1	RBI	Narrow Money (in Rupee Crore)
M3	RBI	Broad Money (in Rupee Crore)
CWP	RBI	Currency with the Public (in Rupee Crore)
BCCS	RBI	Bank Credit to the Commercial Sector (in Rupee Crore)
BCSCB	RBI	Bank Credit – Scheduled Commercial Banks (in Rupee Crore)
NFC	RBI	Non-Food Credit (in Rupee Crore)
ADSCB	RBI	Aggregate Deposits– Scheduled Commercial Banks (in Rupee Crore)
DDSCB	RBI	Demand Deposits – Scheduled Commercial Banks (in Rupee Crore)
TDSCB	RBI	Time Deposits – Scheduled Commercial Banks (in Rupee Crore)
Financial sector Indicators		
CHEQUE	RBI	Cheque Clearance – All India (in Rupee Crore)
SENSEX	BSE	Bombay Stock – 30 price Index, monthly average of the daily closing prices
S&P CNX Nifty	NSE	S&P CNX – 50 price Index, monthly average of the daily closing prices
NET_FII	SEBI	Total value of the net foreign investment inflows during the month (in Rupee Crore)
Rs_Dollar	RBI	The Indian Rupee per US Dollar exchange rate
FORWARD6	RBI	Inter-Bank Forward Premia of US Dollar (6-months)
Price Indicators		
WPI_INR	OEA	Index of Industrial Raw Material prices – WPI based
WPI_MP	OEA	Index of Manufactured Product prices – WPI based
WPI_FA	OEA	Index of Food Articles prices – WPI based
WPI_MIN	OEA	Index of Mineral Oils prices – WPI based
WPI_ALL	OEA	Index of All Commodity prices – WPI based
Real Sector Indicators		
CMV	CMIE	Production of Commercial Motor Vehicles
RAIL	CMIE	Railway Revenue Earning Freight Traffic in Million tonnes
CEMENT	CMIE	Cement Production in Million tonnes
IIP_BASIC	CSO	Index of Industrial Production – Basic Goods
IIP_CAP	CSO	Index of Industrial Production – Capital Goods
IIP_INT	CSO	Index of Industrial Production – Intermediate Goods
IIP_CONG	CSO	Index of Industrial Production – Consumer Goods
IIP_CD	CSO	Index of Industrial Production – Consumer Durables
IIP_CND	CSO	Index of Industrial Production – Consumer Non-Durables
IIP_METAL	CSO	Index of Industrial Production – Basic Metal and Alloy Industries
IIP_ELEC	CSO	Index of Industrial Production – Electricity
IIP	CSO	Index of Industrial Production – General Index
NAGDP	CSO	Non-agriculture GDP at factor cost (1999-00 prices)
External Sector Indicators		
EXPORT	DGCI&S	Total value of exports in terms of US$ million
IMPORT	DGCI&S	Total value of imports in terms of US$ million
NIMPORT	DGCI&S	Total value of non-oil imports in terms of US$ million
CARGO	CMIE	Cargo handled at major ports in Million tonnes
USGDP	BEA	USA Gross Domestic Product
USA_LI	OECD	Index of USA Leading Indicator
EURO_LI	OECD	Index of Euro Area Leading Indicator
CHINA_IIP	OECD	Index of Industrial Production in China
INT_OIL	IMF	International Crude Oil Prices in US$ per barrel
INT_EDIBLE	IMF	International Edible Oil Prices
INT_METAL	IMF	International Metal Prices