Is the Purchasing Managers’ Index a Reliable Indicator of GDP Growth?

Some Evidence from Indian Data

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Abstract

Purchasing Managers’ Index (PMI) surveys have been developed across many countries to provide purchasing professionals, business decision-makers and economic analysts with accurate and timely information to help better understand industry conditions. However, the timeliness and convenience of the PMI data would be of little value if the index does not contain useful information on the economy, especially information beyond that captured by other published data series. Several studies present evidence of the Manufacturing PMI’s ability to predict changes in manufacturing output and real GDP. PMI-based models provide simple yet accurate tools for forecasting headline GDP growth rates in several advanced countries or country-groups, according to the literature. The present study for India suggests that business or policy decisions made early in the quarter on the basis of the PMI data as an indicator of expected economic conditions are likely to be more dependable compared with those based only on official data. This is particularly true of periods with high volatility of economic growth, when the historical values of growth or other indicators like industrial growth fail to capture the current conditions in their entirety. Overall, this study corroborates the results from a study by the Reserve Bank of India (RBI) on inflation forecasting and concludes that the India PMI data may serve the purpose of providing timely and more or less reliable information on the economy, much ahead of officially published data, for assessing economic conditions in the near future.

Introduction

PMI surveys have been developed across many countries to provide purchasing professionals, business decision-makers and economic analysts with accurate and timely information to help better understand industry conditions. The information collected from the surveys is summarised in the form of an index or a group of indices covering relevant areas of business conditions. The organisations which construct the indices, like the Institute for Supply Management (for the ISM US PMIs) or Markit and HSBC (for the HSBC Markit PMIs for a
The advantages offered by PMI data reflect some deficiencies in official economic statistics which result in a situation where analysts attempt to monitor current industry conditions using data that are already out of date when published, which are possibly revised substantially after first publication and which are difficult to interpret against other countries’ data. The PMI surveys have therefore been designed to provide business and policy decision-makers with up-to-date data on which to benchmark performance and base business strategy or policy choices.

However, as Koenig (2002) pointed out, the timeliness and convenience of the PMI data do not count for much if the index does not contain useful information on the economy, especially information beyond that captured by other published data series. The official data series are more comprehensive and have more scientifically accurate samples and methodologies than the PMIs, and therefore better measure actual economic activity. The main value of the PMI surveys is rather in its anticipation of later official data, because it is published significantly earlier than the official data as noted in Bachman (2010). Hence one needs to look into the role of the data thrown up by the PMI surveys in forecasting economic conditions as revealed by subsequently published official data. A vast amount of econometric literature is devoted to studying the forecasting of the state of the economy and much of it relates to forecasting GDP or its growth. One of the basic models of GDP growth still found to fare among the best, and hence considered as the benchmark in most studies of GDP forecasting, is the autoregressive model, where a country’s GDP is predicted by only its own past value(s). However, this ignores a wealth of related information that may have been collected over time, like those given by the indices of industrial production, employment reports, interest rate movements and even PMI indices. As vast amounts of data on the economy started to be collected by national and private agencies, econometric models have been evolving to incorporate these data to improve on the forecasts of GDP. Much of this forecasting literature takes advantage of recent advances in factor models and related techniques that allow researchers to extract useful information from large data sets with many predictors and thus deliver forecasting gains. These models as they evolve are compared
with the benchmark model(s) on the basis of certain statistical criteria. The studies which compare out-of-sample projections from various models focus on backcasts (forecasting last quarter’s GDP before its official release), nowcasts (predicting current quarter GDP) and short-term forecasts (predicting next quarter’s GDP).

Given that PMIs are (coincident) indicators of economic activity, they should be effective for tracking and anticipating GDP developments. Several studies present evidence of the (Manufacturing) PMI’s ability to predict changes in manufacturing output and real GDP. PMI-based models provide simple yet accurate tools for forecasting headline GDP growth rates in several advanced countries or country-groups, according to the literature. In previous studies, Koening (2002) investigates the forecasting properties of PMIs for the US, Godbout and Jacob (2010) for the euro area, and Rossiter (2010) uses PMIs to provide a nowcast of the global economy. All studies conclude that indicator models using PMIs can deliver very accurate near-term forecasts of economic growth. Studies on emerging markets are, however, relatively scarce. In order to understand the usefulness of the Indian PMI in predicting Indian GDP, we look into the bivariate relationship between PMI and GDP growth, and also a multivariate version including the index of industrial production (IIP). We carry out a simple regression analysis to compare the performance of the PMI-based model versus the benchmark autoregressive model in estimating quarterly GDP growth for India. Our results indicate that the India PMIs have some explanatory power for quarterly growth of Indian GDP either on their own or in conjunction with past values of GDP. Though an earlier study had found no additional contribution from the PMI survey for forecasting Indian GDP over that given by past GDP values, our preliminary examination suggests that nowcasting or short-term forecasting exercises based on PMI data are likely to be more accurate than those based on univariate analysis or even that based on past GDP and the IIP data, particularly in periods with high volatility of economic growth when the historical values of growth or other indicators like industrial growth fail to capture the current conditions in their entirety.

**Understanding the Purchasing Managers’ Index**

The US-based Institute for Supply Management (ISM, formerly National Association of Purchasing Management or NAPM) has conducted its survey of purchasing and supply executives in the US continuously since the end of World War II. The survey goes out to executives representing more than 400 companies in 20 manufacturing industries spread across all the US states. These executives are asked about new orders their firms have received and about their firms’ production, employment, inventories, order backlogs, new export orders, and imports of materials and supplies. In each case, executives are asked whether the variable’s current level is higher (or better), lower (or worse), or the same as during the preceding month. To the percentage of executives
The PMIs are based on fact, not opinion, and are among the first indicators of economic conditions published each month. Further, the data are collected using identical methods in all countries so that international comparisons may be made.

who report higher levels of a variable is added half the percentage who report an unchanged level to create a diffusion index for that variable. Thus, an index reading above 50 indicates that more executives are reporting better values for a variable than are reporting worse values and the greater the preponderance of positive responses, the higher the index reading. The CFNAI (Chicago Fed National Activity Index) is another such index for the US economy.

The PMI surveys for a number of economies compiled by Markit are similarly designed to provide time-series variables relevant to a number of important stages in the business cycle, allowing analysts to ascertain the pace of economic growth, to see whether demand and supply imbalances are taking hold, and to see if prices are consequently rising. These PMIs provide an advance indication of what is really happening in the private sector economy by tracking variables such as output, new orders, stock levels, employment and prices across the manufacturing, construction, retail and service sectors. A diagram depicting the relationship between the survey variables and economic activity is provided in the Appendix. PMI data are based on monthly surveys of carefully selected companies numbering over 400 for each country. Questionnaires are completed in the second half of each month and the survey results are then processed by economists from the compiling agency. Respondents are asked to state whether business conditions for a number of variables have improved, deteriorated or stayed the same, compared with the previous month. Survey responses thus reflect the change, if any, in the current month compared with the previous month based on data collected mid-month. The diffusion index is the sum of the positive responses plus a half of those responding “the same”. The (Markit) Manufacturing PMI for a country is a composite index based on five of the individual indices with the following weights: New Orders—0.3, Output—0.25, Employment—0.2, Suppliers’ Delivery Times—0.15, and Stock of Items Purchased—0.1, with the Delivery Times index inverted so that it moves in a comparable direction. An index reading above 50 indicates an overall increase in that variable, and below 50 an overall decrease. The PMIs are thus based on fact, not opinion, and are among the first indicators of economic conditions published each month. Further, the data are collected using identical methods in all countries so that international comparisons may be made.

In many cases, the advantages offered by PMI data reflect deficiencies in official economic statistics, which include:

1 Diffusion indexes have the properties of leading indicators and are convenient summary measures showing the prevailing direction of change.

2 Markit does not revise underlying survey data after first publication, but seasonal adjustment factors may be revised from time to time as appropriate which can affect the seasonally adjusted data series.
1. Infrequent publication
   Many government data series, such as GDP, are published only quarterly. The PMI is published monthly.

2. Delays in publication
   A significant period of time often elapses before official data are published. The PMIs provide data sometimes several months ahead of official series.

3. Revision after first publication
   Even after the official data are published, they are frequently subject to substantial revision. Such revisions mean it is hard to confidently make business decisions based only on these statistics. PMI data, in contrast, are not revised after first publication (with the exception of very minor occasional changes to seasonal adjustments).

4. Lack of comparability with equivalent measures used for other countries
   Not all statistical bodies compile data using the same methodologies. GDP data for the EU are, for example, compiled using significantly different statistical techniques than equivalent data for Japan.

   In contrast, PMIs are released on a monthly basis and very early in the month; they are not revised after publication; they cover almost all private sector economic activity in many countries (including the all-important service sectors); and are produced using the same methodology in all countries, enabling accurate international comparisons. Given these properties, PMI data are understandably often used for GDP forecasting, either in isolation or in conjunction with several other variables. PMIs, at the same time, suffer from certain disadvantages. First, being a diffusion index, while capturing the spread or dispersion of change in economic activity, it does not capture the intensity of the change. Second, since the responses are not weighted for size difference of firms, PMIs may miss an overall shift in economic conditions arising out of movements in a few large firms (Koenig, 2002; Lahiri and Monokroussos, 2013). These disadvantages, however, have not constrained the use of PMI to gauge the strength and direction of economic activity. Before we look at the results of studies on the performance of the PMI data in GDP forecasting vis-à-vis other competing variables, we present a very brief outline of some of the approaches used for such forecasting.

**An Outline of Some Forecasting Models**
In general terms, forecasting entails selecting a set of predictors, and choosing a functional form and estimation method to map this information into the forecasts. There is a wealth of literature on GDP forecasting that covers a number of different approaches. The suitability of each approach depends on the information set available and the timeliness of official data and other indicators, which can differ significantly.
across countries. This section outlines a few of the main approaches, but more comprehensive reviews are available in recent literature, such as Banbura et al (2013).

One common approach to forecasting is to use a basic statistical model, in which GDP growth depends linearly on its previous values and a univariate time series model for quarterly GDP growth is estimated to forecast out of sample GDP. In periods of stable growth this type of model fares rather well, as discussed in Mitchell (2009). But during periods of more volatile growth, the performance of basic statistical models for nowcasting is often poor. Thus short-term forecasting tries to exploit the information contained in various high-frequency indicators, which are typically published earlier than GDP data. Forecast that uses purely quarterly data can also be simply obtained from vector autoregressive (VAR) models with quarterly values of GDP growth and quarterly averages or aggregates of the related monthly indicators (see for example, Robertson and Tallman, 1999).

The “bridge equation” approach was developed to address the challenges of nowcasting when indicators are available for different frequencies (daily, weekly, monthly and quarterly), and are released at different times. In this approach, first, monthly indicators are forecast over the remainder of the nowcast quarter to obtain a quarterly nowcast for that indicator. Second, the resulting nowcasts are used as regressors in the “bridge equation” to obtain the GDP nowcast. The set of indicators could consist of real sector variables, financial variables, survey variables and international economic or survey variables. Traditional bridge equations can only handle a few variables; thus using them limits the number of indicators, potentially discarding useful information, and also requires forecasts of some indicators, which could increase nowcast errors.

A wide range of approaches and models are used by central banks to forecast output in a data-rich environment and to handle the ragged-edge nature of data. More recently, mixed-data sampling (MIDAS) has become a popular approach to nowcasting. The MIDAS approach is a simple way of handling data sampled at different frequencies that does not require indicators of a higher frequency, normally monthly, to be forecast over the quarter. Instead, MIDAS equations are able to directly relate quarterly GDP to the more frequent indicator and its lags. In particular, MIDAS models relate low-frequency variables, such as quarterly GDP growth, to lags of high-frequency variables, such as monthly, weekly or even daily indicators. Since the number of lagged coefficients to estimate is often very large (especially with daily data), a pre-defined functional form for the lag structure of the indicators is usually imposed to reduce the number of parameters to be estimated. The

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1 These predictions can be obtained using various methods, including the expectation maximisation algorithm and univariate monthly autoregressive (AR) models, or by simply assuming a constant reading for the remainder of the quarter.
most commonly used functional form for short-term forecasting is the Almon polynomial, which gives more weights to more recent observations. While imposing a specific functional form reduces the number of coefficients to estimate, it either requires a strong knowledge of the dynamics of the data or may represent a strong assumption for characterising the data-generating process. An alternative MIDAS approach, often referred to as unrestricted MIDAS (U-MIDAS), does not impose a specific functional form on the lag structure, but does assume linearity. Also, in U-MIDAS, the weights given to each individual month are entirely data driven, reflecting the idea that each month of data is not equally important in forecasting GDP. Another interesting feature of U-MIDAS for short-term forecasting is that, unlike other approaches such as factor models or bridge equations, it does not require a forecast of missing months and therefore does not require any assumptions about the behaviour of the indicators in the upcoming months (Lebouef and Morel, 2014). As discussed in Kuzin, Marcellino and Schumacher (2011), an alternative solution to this issue is a mixed-frequency VAR, which can be put in a form that allows for missing values for data not yet available.

Again, directly employing a large model with many variables would require estimating a large number of parameters, which may compromise the estimated model’s forecasting performance. Since Sargent and Sims (1977), factor models have been used for macroeconomic applications to deal successfully with this issue. Factor models can be viewed as a parsimonious alternative to large VAR models. In this approach, common statistical trends (referred to as “factors”), which may reflect common economic influences, are estimated from a large set of data. If there is a high degree of comovement among the GDP and the indicators series, then most of the movement in the series of interest can be captured by a few factors. By extracting common patterns (factors) from multiple data series, factor models can reduce the dimensionality of the data and thus the complexity of the estimation process. Dynamic factor-models (DFMs) are viewed as a particularly efficient means of extracting information from a large number of data series, so that instead of a single indicator variable or a group of indicator variables, one may contemplate the use of the most important factors extracted from the whole data set for forecasting; the factors can be considered as the driving forces of the economy. The latent factors follow a time series process, which is commonly taken to be a VAR. Studies on bridge equation models have proposed to use factors extracted from large

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4 Sargent and Sims (1977) showed that two dynamic factors could explain a large fraction of the variance of important US quarterly macroeconomic variables, including output, employment, and prices.
5 Dynamic factor models were originally proposed by Geweke (1977), as a time-series extension of factor models previously developed for cross-section data. The extended framework allows a relatively limited number of structural shocks to cause comovements among macroeconomic variables at all leads and lags.
monthly datasets to perform bridging, which exploit a large number of indicators within the same model (bridging with factors) (Giannone, Reichlin and Sala, 2004).

Again there may be different approaches to extracting the factors using various variable reduction procedures. The nowcasting literature often employs a principal components (PC) estimation following Stock and Watson (2002). Principal component analysis is appropriate when there are measures on a large number of observed variables, where several of them may be highly correlated. The analysis helps to develop a smaller number of artificial variables (called principal components) that will account for most of the variance in the observed variables. The principal components may then be used as predictor variables in subsequent analyses. An additional challenge that comes with this task of extracting the maximum amount of useful information from these large data sets in real time is that as new data releases arrive throughout the quarter they are incorporated at various times into these panels, which are thus unbalanced panels, or have jagged edges. The Kalman filter (KF) estimator deals efficiently with ragged edges, caused by the non-synchronous flow of data releases, by replacing the missing observations with optimal predictions based on the entire set of monthly indicators. The Kalman filter (KF) estimator deals efficiently with ragged edges, caused by the non-synchronous flow of data releases, by replacing the missing observations with optimal predictions based on the entire set of monthly indicators. Theoretical econometric research on DFMs over the past decade has made a great deal of progress, and a variety of methods are now available for the estimation of the factors and of the number of factors. Initial estimation models using the maximum likelihood estimation (MLE) and the KF provided optimal estimates (and optimal forecasts) of the factors given the model assumptions and parameters. However, estimation of those parameters entails nonlinear optimization, which historically had the effect of restricting the number of parameters, and thus the number of series, that could be handled. This led to the development of nonparametric estimation using cross-sectional averaging methods, primarily principal components and related methods. If the number of series is sufficiently large, then the factors are estimated precisely enough by PC to be treated as data in subsequent regressions. A recently developed method for estimating the factors merges the statistical efficiency of the KF approach with the robustness and convenience of the PC approach (Stock and Watson, 2010). Another area of development in the nowcasting literature has been estimating densities, rather than only producing a central estimate for GDP growth. A density nowcast provides the likelihoods that a model would attach to the different outturns of GDP growth occurring. This approach is a way of formalising the uncertainty around the outlook for the economy.

6 The Kalman filter is an efficient recursive filter that estimates the internal state of a linear dynamic system from a series of noisy measurements. It is used in a wide range of engineering and econometric applications from radar and computer vision to estimation of structural macroeconomic models.
Some Evidence from Country Studies

Survey variables and the PMI in particular have been shown to have forecasting power for GDP and the business cycle in various country studies using some of the methods mentioned above or their variants. These studies often compare various methods of estimation or forecasting among themselves or against a benchmark model. Improvements in forecasting power are generally measured by some statistical criteria like the RMSE (root mean square error). We summarise below some results from selected studies, which include PMIs as one of the indicators or predictors of GDP, in chronological order for each country/country-group.

United States

In one of the early studies on the role of survey indices as indicators of GDP growth, by Koening (2002), regressions of manufacturing output and quarterly real growth on the ISM PMI, from 1983 to 2002, yield the results that the long-run impact of a 1-point increase in the PMI is 0.61 percentage points for US manufacturing output growth and 0.27 percentage points for real GDP growth. More importantly, the study also determines that the PMI has predictive power for GDP growth beyond the measures of economic activity like available jobs, sales, and industrial production data. The study concludes that the ISM PMI deserves the attention it receives in the financial and business press as an indicator of changes in real economic activity. Among similar studies, Harris et al (2004) also found that the ISM is effective in tracking movements of GDP in real time, i.e., considerably ahead of the GDP release. They calculated that the ISM index improves the current quarter forecast of GDP by about 12 per cent, and the one-quarter-ahead forecast of GDP by 31 per cent. In a comparative analysis, Banerjee and Marcellino (2006) carry out empirical evaluation of three alternative approaches to information extraction from a large data set for forecasting, namely, the use of an automated model selection procedure, the adoption of a factor model to summarise the available information, and single indicator based forecast pooling. Using 74 GDP growth indicators from the OECD Main Economic Indicators database, which includes several ISM PMI sub-indices and the CFNAI, they find that ex post, i.e., assuming future values of the indicators are known, univariate leading indicator models are better than autoregressions, but the best indicator changes over time. The results are robust to the use of rolling estimation and choice of forecasting horizon and more importantly, ex ante the indicators can outperform the autoregressions more than 80 per cent of the time. Overall, single indicator forecasts in general outperform more sophisticated multivariate methods (when using the RMSE-h loss function for evaluation). They conclude that gains from simplicity are mostly larger than those from the use of a larger information set.

Among recent studies, D’Agostino and Schnatz (2012) demon-
A real-time out-of-sample forecasting exercise linking the PMI and SPF surveys to US GDP growth over a sample period of more than 40 years shows that both indicators convey valuable information for assessing current economic conditions. They also note that combining the information included in both surveys further improves the accuracy of both, the PMI and the SPF-based forecast. They also find that the non-manufacturing indices have significant added value in nowcasting GDP. Again, Lahiri and Monokroussos (2013) assess the usefulness of ISM indices in nowcasting US GDP when large unbalanced (jagged edge) macroeconomic data sets are used in real time to generate the forecasts. Given the plethora of variables that could be used for that purpose they ask: what is the marginal impact of the ISM variables, given all the other information that is available in real time? Using data from 1965 to 2011, they base their conclusions on a simple indicator model following Koenig (2002), and the more advanced MIDAS regressions and DFMs. They find evidence that the PMI indicators do help improve the nowcasts of current quarter GDP growth, as the quarter unfolds in real time.

**Euro Area**

For the euro area, Barhoumi et al (2008) consider a range of models for short-term GDP forecasting, including traditional bridge equations and DFMs. First, they examine the forecast performance under the real-time flow of data releases, taking account of the non-synchronous release of monthly information throughout the quarter. Second, they use 10 large datasets; in addition to the euro area as a whole they consider datasets from six euro area member states from January 1991 up to mid-2006, and from three new member states of the EU, but with a shorter sample period. They evaluate the forecast performance of the various models over the period from Q1 2000 to Q4 2005. The main finding obtained for the euro area countries is that bridge models, which exploit timely monthly releases including those from PMI surveys, fare considerably better than quarterly models. Among those, DFMs, which exploit a large number of releases, do generally better than averages of traditional bridge equations. The study suggests that the idea of using factors to bridge monthly with quarterly information in short-term GDP forecasting is promising and should be more systematically explored in the Eurosystem.

Godbout and Jacob (2010) study the usefulness of the monthly PMIs in predicting short-term real GDP growth in the euro area, Japan, the United Kingdom, and China, as well as in the world economy. They try to assess whether PMIs can help predict real GDP growth at the margin when other traditional monthly indicators are available. They build simple indicator models and verify whether the addition of PMIs improves the in- and out-of-sample predictions. For all economies,
PMIs turn out to be significant explanatory variables and to substantially improve the accuracy of predictions. Lombardi and Maier (2011) evaluate forecasts for the euro area in data-rich and data-lean environments by comparing three different approaches: a simple model based just on PMIs, a DFM with euro area data, and a DFM with data from the euro area plus data from national economies. They estimate backcasts, nowcasts and forecasts for GDP, components of GDP, and GDP of all individual euro area members. They examine forecasts for periods of low and high economic volatility; more specifically, they consider the period 2002–2007, which corresponds to the “Great Moderation” and also the “Great Recession” from 2008–2009. They find that all models consistently beat naive AR benchmarks, and overall, the DFM tends to outperform the PMI model at times by a wide margin. However, the accuracy of the DFM can be uneven as forecasts for some countries have large errors. The PMI model clearly dominates for some countries or over some horizons; this is particularly pronounced over the Great Recession, where the PMI model dominates the DFM for nowcasts.

Leboeuf and Morel (2014) use U-MIDAS regressions for the evaluation of the usefulness of a wide range of indicators in predicting short-term real GDP growth. In their forecasting evaluation exercise they compare pseudo out-of-sample predictions of quarter-over-quarter real GDP growth obtained using the U-MIDAS model with the realized values. First, a pseudo real-time data set is assembled using final-vintage data as of Q1 2013. Second, they estimate the U-MIDAS regression models over the sample from Q1 1999 to Q4 2009, and forecast real GDP growth two quarters ahead. Using an expanding window approach, they obtain out-of-sample forecasts between Q1 2010 and Q1 2013. In line with previous studies, the results suggest that the PMI is among the best-performing indicators to forecast real GDP growth in the euro area.

Among EU country studies, VAR models based on forward looking surveys are found to best forecast Swedish real GDP growth by Andersson (2007), who examines whether VAR models that use forward looking surveys as explanatory variables perform better than random walk and pure autoregressive models for forecasting Swedish real GDP growth using data from 1993 to 2006. Bell et al (2014) report that in addition to official data, survey indicators have typically improved nowcasts for the United Kingdom. According to their study, as the recession increased output volatility substantially, the largest error from the benchmark model occurred in Q4 2008, when output contracted sharply. Nowcasts that incorporated data from the business surveys performed better in the more volatile period. However, the nowcasts produced by Bank of England (BoE) staff have, on average, outperformed those from the weighted survey model and a simple AR

7 Truncated to contain only observations that would have been available when the forecast would have been made in real time.
model over the period 2004–13. This is because the BoE estimates have reduced weightage on surveys in periods when the surveys may have been judged to be over- or under-stating GDP growth.

**Japan**

Godbout and Jacob (2010) find the Japan PMIs to be significant explanatory variables in the GDP equation and to substantially improve the accuracy of predictions of GDP. The recent study by Leboeuf and Morel (2014) mentioned above finds that consumption indicators and business surveys (like the PMI and the Economy Watchers Survey) have the most predictive power for Japanese GDP.

**Emerging Markets**

Godbout and Jacob (2010) find China Manufacturing PMIs to be significant explanatory variables in the Chinese GDP equation and to substantially improve the accuracy of predictions of GDP. Pedersen (2010), Maier (2011) and Matheson (2011) are among the few attempts of nowcasting economic activities in emerging markets. Pedersen (2010) nowcasts Chilean GDP by extracting signals from monthly indicators of economic activity; the results show that with respect to the final readings of growth rates, signals which are as reliable as those of the first GDP release can be extracted from the IMACEC survey index. Further, compared with in-sample nowcasting the final GDP with historical data, the forecast performance improves significantly with each month of available IMACEC data. Measured by the root mean square nowcast error (RMSNE), the out-of-sample performance also improves as more monthly data becomes available. Maier (2011) evaluates different approaches for using monthly indicators to nowcast and forecast Chinese GDP. The study evaluates different ways to incorporate information from high-frequency indicators to project current and next quarter GDP of the Chinese economy using data since Q3 1999 and conducting out-of-sample forecasts for Q2 2008–Q4 2010. The results show the China (Markit and national manufacturing) PMI and some of the component indices to be highly significant within the indicators based model in which several other official data, like industrial production and exports, are also considered. Matheson (2011) predicts economic activity of a large number of countries, including emerging markets at a monthly frequency by utilising a wide range of economic time series including PMIs, and consumer and business confidence surveys. The author nowcasts GDP of a large number of countries using various models and finds that for India (along with Australia and Saudi Arabia), factor models based on a large data set perform poorly compared with simpler models such as pooled bridge model with limited indicators.

**Global Economy**

Rossiter (2010) constructs simple mixed-frequency forecasting equations for quarterly global output, imports, and inflation using the
monthly global PMI from 1999 to 2009. When compared against two benchmark models, the results show that the PMIs are useful for forecasting developments in the global economy. The results suggest that the PMI-augmented models are superior to the benchmarks, regardless of the months of PMI data available; however, as the forecasts are updated throughout the quarter with the monthly release of the PMI, forecasting performance generally improves. An analysis of the forecasts over the period of the Great Recession (in particular, Q4 2008 to Q2 2009) shows that while models which include the PMI indicators did not fully capture the sharp deterioration in the global economy, they nevertheless improved the forecasts relative to the benchmark models. This finding highlights the usefulness of such indicators for short-term forecasting.

Stratford (2013) shows that since the onset of the financial crisis, the indicator models with PMIs have performed better than the simple AR benchmark. Before 2008, however, when growth was fairly stable, the predictive power of the indicators over and above a simple AR model was fairly low. Between 1999 and 2007, when global growth was fairly stable, the indicators did not contain much more information than a simple AR model. But when there are larger swings in the data the indicators tend to have a higher correlation with global activity. That was especially true during the sharp fall and recovery in global growth in 2008–09. On average, since 2008, the most accurate nowcasts were produced by combining the signal from a range of indicators. The nowcasts from the combined indicator models tracked the sharp fall and recovery in global growth through 2008 and 2009 much more closely than those from the simple benchmark or any of the individual indicator models.

A study by Drechsel et al (2014) analyses the performance of the IMF World Economic Outlook forecasts for world output growth and GDP growth of both the advanced economies and the emerging and developing economies. With a focus on the forecast for the current and the next year, they examine whether IMF forecasts can be improved by using leading indicators with monthly updates. For the world indicators they select the Global Composite PMI, Global Manufacturing PMI, and OECD Leading Indicators. Using a real-time dataset for GDP growth and for the indicators they find that some simple single-indicator forecasts on the basis of data that are available at higher frequency can significantly outperform the IMF forecasts if the publication is only a few months old. They find that the OECD leading indicator and the PMI (manufacturing) can significantly improve the forecast quality of the IMF economic outlook.

Overall, the studies conducted over various geographies and time periods, rigorously using different (GDP or growth) forecast models and evaluation techniques, definitely suggest that PMIs are among the best-performing indicators to forecast real GDP growth. Most research studying the single indicator based approach, pooling of various
indicators approach, or the bridge equation approach to GDP forecasting find PMIs to be significant explanatory variables in the quarterly GDP growth equation and to substantially improve the accuracy of GDP predictions. This result also holds true across different approaches to nowcasting based on VAR, MIDAS equations, indicator pooling or DFMs, all with large data sets. The literature for advanced economies shows unequivocally that PMI surveys, which provide the earliest information, contribute to an improvement in the nowcasting in the early part of the quarter, before hard data like industrial production and retail sales become available. The studies based on more advanced models like variants of the DFM, or those comparing sophisticated models with single indicator models or indicator pooling, also bring out the fact that more data does not always yield better forecasts, and that the very simple and easy to maintain, lean-data PMI model is not always easily outperformed by the much more data-intensive models. This is particularly true of countries where official data are subject to significant revisions. Further, the studies suggest that the information content of any of the indicators can fluctuate greatly over time. Survey-based measures can have considerable advantages in responding to changes during very volatile periods, whereas forecasts based on traditional time series models often exhibit a higher degree of persistence and hence produce less accurate results.

The PMI and GDP Growth Relationship for India

An extensive study on GDP nowcasting for India has been carried out by Bhattacharya et al (2011). They evaluate alternative methods that exploit timely monthly releases to compute early estimates of current quarter national accounts aggregates (nowcasting) with data up to 2010. The evaluation is conducted using an out-of-sample forecasting exercise. The authors perform a pseudo real-time simulation: by taking into account the actual publication lags of the various monthly series, they replicate the information set available to the policymaker at each point in time, and nowcast the upcoming GDP data release. The nowcasting analysis is restricted to two measures of growth: GDP excluding agriculture (GDPXagri), and GDP excluding agriculture and other services (GDPXoth). Apart from examining which model(s) perform best for forecasting India’s GDP growth, they investigate for the first time the effective usefulness of Indian survey data in nowcasting GDP. For each sub-sector of GDP, relevant monthly indicators are identified and bridge models estimated on the year-on-year growth rate of quarterly aggregates of monthly variables to predict the year-on-year growth rate of GDP. They find that, despite its timeliness, the PMI survey data does not improve the nowcasting of the benchmark AR and Naive models. However, their detailed results, comparing indicator models on the basis of RMSE, do show that the PMI performs marginally better than IIP manufacturing in predicting GDPXagri. Given the not so definite results for the India study on GDP
forecasting, we look into the explanatory power of the India PMI for the Indian GDP.  

In this section we explore in some detail the relationship between India’s quarterly GDP growth rate and the Manufacturing PMI for India, with the IIP data included for additional information. As the PMIs measure the changes in economic conditions in each month in comparison with the previous month, quarterly averages of the PMIs should be able to predict quarter-on-quarter changes in GDP. Further, when IIP data is available, quarterly averages of the month-on-month changes in the IIP should also have some explanatory or predictive power for quarterly GDP growth. GDP and IIP data for India are provided by the Central Statistics Office (CSO). However, as seasonally adjusted quarter-on-quarter growth rates of real GDP are not available from official estimates, we use the quarterly growth rates provided by the OECD for this purpose as this series is also adjusted for seasonal variation. The oft-quoted HSBC India Manufacturing PMI compiled by Markit is used for this study. The sample period for this study ranges from 2008 to 2014, covering a period when growth has been relatively more volatile after the onset of the global financial and economic crises. The India PMI, a diffusion index, is based on replies to monthly questionnaires sent to purchasing executives in over 500 manufacturing companies. The panel is stratified geographically and by SIC (Standard Industrial Classification) group, based on industry contribution to Indian GDP. As stated earlier, the Manufacturing PMI is a composite index based on five of the individual diffusion indices with the following weights: New Orders—0.3, Output—0.25, Employment—0.2, Suppliers’ Delivery Times—0.15, and Stock of Items Purchased—0.1, with the Delivery Times index inverted so that it moves in a comparable direction. Survey respondents are asked whether their output (or any other relevant variable) has risen, fallen or remained unchanged over that of one month ago. The unweighted net balance of survey responses is converted into a (seasonally adjusted) diffusion index with a level of 50 being the threshold value between contraction and expansion:

$$PMI_t = \frac{(I + 0.5N)}{(I + N + D)} \times 100$$

where “I” is the number of respondents reporting increases, “N” is the number of respondents reporting no change and “D” is the number of respondents reporting decreases. A reading above 50 in the diffusion index indicates economic expansion, while a reading below 50 indicates contraction.

8 Particularly, as an RBI study on forecasting inflation for India had indicated that the PMI price indices are good indicators and have significant predictive power of the changes in WPI–All commodities and WPI–Non-food manufactured products. The analysis was carried out using both Ordinary Least Squares (OLS) estimates and the Autoregressive Distributed Lag (ARDL) approach to cointegration for the period April 2005 to October 2012 (Khundrakpam and George, 2013).

9 Markit is a leading global diversified provider of financial information services. HSBC is one of the world’s largest banking and financial services organisations.
We study the bivariate relationship between PMI and GDP growth through regressions. We then include IIP data to see whether the PMI has additional explanatory power for GDP over and above that provided by the past values of GDP and contemporaneous IIP data taken together.

The movements of India’s quarterly GDP growth rates and average PMI for the quarter, depicted in Chart 1, show a correspondence between the two series; this is borne out by a moderately high correlation coefficient of 0.51 for the two series. This leads us to further investigate the relationship between the two variables, particularly to see whether the PMI series, which is published much in advance of the GDP release for any quarter, has any explanatory power for the GDP growth rate.

In this section, we first estimate the univariate model of GDP growth, and then move on to study the bivariate relationship between PMI and GDP growth through standard regressions. We then include more rigorously calculated and officially published IIP data to see whether the PMI has additional explanatory power for GDP over and above that provided by the past values of GDP and contemporaneous IIP data taken together.

The univariate model estimated here is a first order autoregressive model (AR), where GDP growth depends solely on its own lagged value of the previous quarter along with an error term:

$$y_t = a + b_1 y_{t-1} + e_t$$

where, $y_t$ denotes GDP growth.

Next we estimate simple, linear indicator-based models either only with single indicators or with an auto regressive term, referred to as AR+X models, with the PMIs as the indicator of GDP growth along with a lagged value of GDP growth. An obvious issue in estimating GDP based on the PMI is the different frequencies of the target variable.

10 In comparison, for Brazil this correlation is as high as 0.75.
and its predictors as the GDP growth rate is a quarterly figure, whereas PMI variables are monthly indices. The simplest thing to do is to construct quarterly averages using the three observations on PMI during the quarter.\textsuperscript{11} An alternative approach is to regress GDP growth on each of the quarter’s three-monthly PMI indices separately. In what follows we have termed these three monthly PMIs as far month PMI (FM), mid-quarter month PMI (MQM), and near month PMI (NM), with FM being the PMI for the first month of the quarter, MQM the PMI corresponding to the second month, and NM being the PMI reported for the final month of the quarter in question. The quarterly average of the three monthly PMIs, FM, MQM and NM, is referred to simply as PMI. The variation in quarterly PMIs is termed PMIQC.

The PMI-based AR+X models are estimated as:

\[ y_t = a + b_1 y_{t-1} + b_2 x_t + e_t \quad \text{(AR-PMI/FM/MQM/NM/PMIQC)} \]

where, \( x_t \) may represent PMI\(_t\), which is the (equally) weighted average of monthly PMIs for the \( t \)th quarter; the individual monthly PMIs for the quarter, namely, FM\(_t\), MQM\(_t\) and NM\(_t\); or the change in quarterly average PMI, namely, PMIQC\(_t\).

We also estimate the equation with all three monthly PMIs as indicator variables:

\[ y_t = a + b_1 y_{t-1} + b_2 FM_t + b_3 MQM_t + b_4 NM_t + e_t \quad \text{(AR-PMIAll)} \]

To assess the marginal contribution of PMI data in explaining India’s GDP growth, when IIP growth is included as an indicator, we run additional regressions with quarterly averages of both monthly PMIs and IIP growth rates for the quarter:

\[ y_t = a + b_1 y_{t-1} + b_2 IIP_t + b_3 PMI_t + e_t \quad \text{(AR-PMI-IIP)} \]

The results of our regression analyses (summarised in Table 1) show that the AR coefficients (up to 4 lags) are not significant in the AR model; hence for India, the quarter-on-quarter changes in GDP cannot be explained by the AR(1) model, considered a benchmark in several studies. Therefore, we look into the indicator-based model with PMIs as indicators of GDP growth, disregarding the autoregressive term. We find the coefficient of the PMIs to be significant in the indicator based models when different variants of the PMI, namely, the average PMI for the quarter (PMI), all the three individual PMIs (FM, MQM and NM) and the quarterly variation in PMI (PMIQC and PMI-PMIQC) for the specified quarter, are considered. However, when the three PMIs are individually included in the regression (PMIAll), only the coef-

\textsuperscript{11} As explained in Lahiri and Monokroussos (2013), one way of addressing this issue is to employ a simple and intuitive approach such as that of Koenig (2002) where the quarterly PMI is a weighted average of the levels of the monthly PMI index coming from this quarter and last quarter—an intuitive transformation, given that GDP growth measures the percentage change from last quarter to this one.
### Table 1
Some Results from the Regression Analyses

#### Panel A: Estimates from Quarter on Quarter Changes

<table>
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<tr>
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<th>Standard Error</th>
<th>t Stat</th>
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<td>0.262</td>
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<td>Intercept</td>
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<td>0.071</td>
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<td>PMI_NM</td>
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<td>PMI_MQM</td>
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<tr>
<td>PMI_FM</td>
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<td>0.418</td>
</tr>
<tr>
<td>Intercept</td>
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<td>4.240</td>
<td>2.012</td>
</tr>
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<td>0.187</td>
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<tr>
<td>PMI_FM</td>
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#### Panel B: Estimates from the Moving Average Series

<table>
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<th>Specification</th>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
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<td>IndiaPMI3QMA</td>
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<td>0.056</td>
<td>2.134</td>
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<td>Intercept</td>
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<tr>
<td>GDP3QMA-L</td>
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<td>0.044</td>
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<tr>
<td>Intercept</td>
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<td>0.185</td>
<td>2.014</td>
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<tr>
<td>GDP3QMA-MqM</td>
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<td>0.039</td>
<td>1.313</td>
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<tr>
<td>Intercept</td>
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<td>0.153</td>
<td>2.053</td>
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<tr>
<td>GDP3QMA-NM</td>
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<td>0.035</td>
<td>2.461</td>
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<tr>
<td>Intercept</td>
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<td>0.048</td>
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<td>IndiaIIP3QMA</td>
<td>0.051</td>
<td>0.055</td>
<td>0.941</td>
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</table>
ficient of NM is significant, while the coefficients of MQM or FM are not significant. Further, for all the above regressions, though the PMI coefficients are significant in explaining quarterly variations of GDP, the explanatory power as given by the R-square values are quite low, indicating that the predictive power of the model may not be very high.

At this stage we look into the explanatory power of the IIP growth rates for GDP growth. Chart 2, which depicts the trends in month-on-month changes in both the IIP and the PMI, shows the high degree of volatility in the monthly IIP growth rates. The bivariate relationships of the quarterly growth rates of GDP with the PMI and the IIP, depicted in the scatter plots in Charts 3.1 and 3.2, confirm

CHART 3.1
Scatter Plot of India’s Quarterly GDP Growth Rate and Average PMI for the Quarter

The bivariate relationships of the quarterly growth rates of GDP with the PMI and the IIP confirm a stronger relationship between the PMI and quarterly GDP growth as compared with IIP and GDP growth.

12 In this case one needs to find out whether considering a longer sample period leads to different results, as we are including a higher number of regressors with a relatively smaller sample. We have experimented with some other combinations of PMI values, using the last quarter’s PMI values (in line with Koenig, 2002), but the results did not improve significantly.
We consider a 3-quarter MA series of quarterly GDP growth, along with 3-quarter MA series for PMI and IIP growth rates. We then re-estimate the models with all the MA series. The results show that the single AR term is indeed significant in the AR model and all the PMIs are significant in the single indicator based models.

A stronger relationship between the PMI and quarterly GDP growth as compared with IIP and GDP growth. As for the regressions for quarter-on-quarter GDP growth with both PMI and IIP as indicators, the quarter-on-quarter IIP growth rate is not found to have significant explanatory power for GDP growth. Thus, the PMI (or its quarterly changes) does have some explanatory power for quarter-on-quarter GDP growth rates, even when lagged GDP or the IIP growth rates do not come across as significant explanatory variables.

It is most likely that the rather high quarterly fluctuations in GDP in our sample (which encompasses a period of volatile growth) lead to the finding that the AR model is not appropriate for explaining quarter-on-quarter GDP growth. Hence, at this stage we construct a smoothed GDP series to see whether this is a possibility. We consider a 3-quarter moving average (MA) series of quarterly GDP growth, along with a 3-quarter MA series both for PMI and IIP growth rates. We then re-estimate the AR and AR+X models with all the MA series.

The results of this set of regressions show that the single AR term is indeed significant in the AR model and all the PMIs are significant in the single indicator based models. When we consider the AR+X model with the PMI series, only the (average) PMI remains a significant explanatory variable. However, when the PMI NM, MQM and FM are considered separately in the AR+X framework, both NM and the AR term are significant, while coefficients of MQM and FM are both not significant in their respective regression equations. Next we consider both the IIP growth rates and the PMI (MA) series as indicators of GDP growth. Interestingly, we find that the PMI remains a significant variable in the GDP growth equation, even when IIP growth does not seem to con-

13 Neither does the quarterly average of the month-on-month IIP growth rates have any significance in the quarterly GDP growth equation.
14 For the AR model, the single lagged value of the MA series is chosen so that there is no overlap in the GDP MA series and its lagged values; for example, the average of the first, second and third quarters of 2009 is the lagged value chosen corresponding to the MA value of the fourth quarter of 2009 and the first and second quarters of 2010.
tain any additional information. This is not entirely unexpected as the PMI surveys cover certain areas of economic expectations or activities contributing to output, which are not covered by industrial growth alone. Further, the lack of a stronger relationship between GDP and IIP growth could be explained by the fact that the IIP series is not seasonally adjusted, while both the PMI and GDP series are. Seasonal factors play an important role in employment and growth dynamics in India; this may be better captured by the seasonally adjusted PMIs.  

Next we determine which of our estimated regression models perform better in terms of explaining quarterly GDP growth. The estimated values from all the models presented in Chart 4 give an idea about the performance of the different models. Chart 4 suggests that while the autoregressive model may fail to capture any sharp changes in GDP, the PMI based AR+X models can sometimes over- or under-estimate such fluctuations. The average PMI and the near month PMI (NM) based estimates often come out as the closest to the actual values of quarterly GDP growth, considering respectively, the quarter-on-quarter changes (QoQ) and the moving average of quarterly growth (MA).

However, for a formal appraisal of model performance, we look at both the root mean square error (RMSE) and the mean absolute error (MAE), measures which are regularly employed in model evaluation studies. The RMSE is the square root of the variance of the residuals. It indicates how close the observed data points are to the model’s estimated values; thus lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction. Similarly, the MAE measures the average magnitude of the absolute value of the errors in a set of estimates. The MAE summarises performance in a way that disregards the direction of over- or under-prediction.  

The MAE and the RMSE are calculated as:

\[ \text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |e_i| \]  

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} e_i^2} \]  

where, \((e_i, i = 1, 2, \ldots, n)\) are the model errors or the difference between the estimated and the true values.

The comparison of the different models for prediction of GDP values is presented in Table 2, where for the QoQ regressions the PMI...
CHART 4
India's Quarterly GDP Growth Rates and Estimates from Various Models

[Chart showing quarterly GDP growth rates and estimates from various models, including India GDP QoQ, NM, PMI, PMI-PMIQC, PMI-IIP, PMIAI, and AR-PMI.]
model is taken as the benchmark, while for the MA equations it is the AR model. For explaining the QoQ changes, a combination of the level of (quarterly) PMI and its variation (PMI-PMIQC) as the indicators of GDP growth, performs the best among all the options. Though there is not very much to choose between the different PMI models, the average PMI (PMI) as an indicator seems to outperform the others, excepting the PMIAII in terms of the MAE criteria. Thus either PMI or PMI-PMIQC can be used to estimate quarterly GDP from a simple linear regression model, though the explanatory power remains rather low. This may be well be related to the volatility of quarterly growth in our relatively short sample period, which corresponds to the post-2007 financial and economic crises years. For the MA regressions, all the three models outperform the AR model in terms of the RMSE criteria and in terms of the explanatory power, which has improved significantly, as expected, over the QoQ model. The AR+X model with the near month PMI (NM) outperforms the rest in terms of all the criteria.

Thus, in this empirical exercise, overall we find that the coefficients of the PMIs (quarterly average, individual month, or quarterly variations) are significant in all the regressions for quarterly GDP growth (QoQ and MA), while the IIP growth rates are not significant in any of the regressions, and the AR model is only applicable to the smoothened growth series (MA). The PMI model with the average PMI and its quarterly variation fares the best for explaining the QoQ growth rates, though with low explanatory power. For the smoothened series, a model combining the past values of GDP changes and the near month PMI is the best for estimating quarterly (MA) GDP variations.

<table>
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<tr>
<th>Specification</th>
<th>Adjusted R-square</th>
<th>RMSE</th>
<th>Rank</th>
<th>MAE</th>
<th>Rank</th>
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<td>2</td>
<td>1.000</td>
<td>3</td>
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<td>1.013</td>
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</table>

Table 2: Comparison of Different Specifications on the Basis of the RMSE and MAE Criteria

Panel A: Specifications for Quarter on Quarter Changes

Panel B: Specifications for the Moving Average Series
Concluding Observations

The considerable delay in the publication of national accounts data, stemming from the vastness and complexities of estimation, underlines the need for reliable and timely information about current and future economic conditions for business analysts and decision makers, as well as economic and monetary policymakers. Business survey based indicators, which are compiled from a qualitative assessment recorded in interviews, are only indirectly related to growth dynamics in the official measures of GDP. However, certain advantages of these survey based indices, the chief among them being their timeliness, have led to extensive use of these indices like the PMI, for the purpose of assessing GDP growth in the near future. Consequently, with the development of the forecasting literature, the usefulness of the PMIs in GDP forecasting (or nowcasting) has also been studied across several economies. Most studies have confirmed that the PMIs considered on their own are extremely useful in predicting GDP growth, particularly in the near future (current and following quarter). Further, PMIs are found to provide additional predictive power for GDP growth, even when considered in conjunction with other variables like past values of GDP growth rates, industrial production, and retail sales.

In India, official estimates of GDP are released with considerable delay; the first release of quarterly GDP growth is published approximately seven to eight weeks after the end of the reference quarter. This delay leads most analysts to look elsewhere to form their views, taking cues from indicators like the official IIP figures, which are also available with a considerable lag, or from the movements of coincident indicators like the HSBC (Manufacturing) PMIs compiled by Markit, which are consistently available at the beginning of each month. These indicators are available at a higher frequency, but may provide only a partial representation of overall economic activity. Hence in this study we try to determine whether a simple and easy to maintain PMI model can be used to provide a fair idea about GDP growth in India, much before official data on quarterly growth are released.

The results of this study, which incorporates recent data corresponding to a period of more volatile growth as opposed to an earlier study with Indian data (Bhattacharya et al., 2011), are somewhat in agreement with studies on several other economies, where the simple PMI based model is found to perform better than the autoregressive model and some other models in a data rich environment, in anticipating near-term GDP growth. Our results show that the India Manufac-

17 The reference figures for quarterly GDP are computed from the production side aggregating estimates of the Value Added in each sector of the economy, with such aggregates relying on various proxy indicators of economic activity. The estimation of GDP is generally complex and difficult to replicate as the CSO may have access to additional sources not available to the public, and because the exact estimation methodology remains confidential (Bhattacharya et al., 2011).
turing PMI data serve the purpose of providing some additional information on current economic growth over that embedded in its own past values and other available higher frequency official indicators like the IIP growth rates. The low explanatory power of the models is a concern for forecasting exercises. However, given the lack of explanatory power of the autoregressive terms and the growth rate of other official data like the (non-seasonally adjusted) IIP, for quarter-on-quarter changes in GDP, the PMI based models seem to be the best alternative for gauging near term quarterly growth. PMI-based models have the added advantage that they are comparable across a large number of economies for which such PMIs are estimated. Given the finding by Rossiter (2010) that for India (along with some other economies) data-rich models may not work too well, the simple PMI model comes out as a valuable alternative. Our finding that the PMI or the AR-PMI model ranks the highest among the considered alternatives, is also consistent with the findings by Stratford (2013), who shows that since the onset of the financial crisis, the indicator models with PMIs have performed better than the simple AR benchmark.

Thus our study on the quarter-on-quarter GDP growth rates for India suggests that business or policy decisions made early in the quarter on the basis of the PMI data as an indicator of expected economic conditions are likely to be more dependable compared with those based on official data. This is particularly true of periods with high volatility of economic growth, when the historical values of growth or other indicators like industrial growth fail to capture the current conditions in their entirety. Overall, this study corroborates the results from an RBI study (Khundrakpam and George, 2013) on inflation forecasting and concludes that the India PMI data may serve the purpose of providing timely and more or less reliable information on the economy, much ahead of officially published data for assessing economic conditions in the near future.18

18 As the sample period, methodology and the variables considered are different, this study does not directly contradict that by Bhattacharya et al (2011).
APPENDIX
Stages of Economic Activity and Chosen PMI Variables

Source: Markit Financial Information Services.
References


Markit (2014), Interpreting PMI Survey Data—Exploring the inter-relationships of selected economic indexes from the PMI surveys.


