Special Feature A

Enhancing Surveillance of the Singapore Economy: The Nowcasting Approach

Introduction and Motivation

Real-time policy analysis and formulation depends critically on an accurate and timely reading of the evolving state of the economy. At present, EPG employs a suite of approaches for ongoing surveillance of the Singapore economy. As shown in Chart 1, these approaches can be broadly classified as either model-based or spreadsheet-based. Macroeconometric models such as the Monetary Model of Singapore (MMS) and the Satellite Model of Singapore (SMS), which were featured in previous *Reviews*, fall into the first category, providing economy-wide perspectives of the interactions between aggregate demand, supply, and prices in a consistent framework.

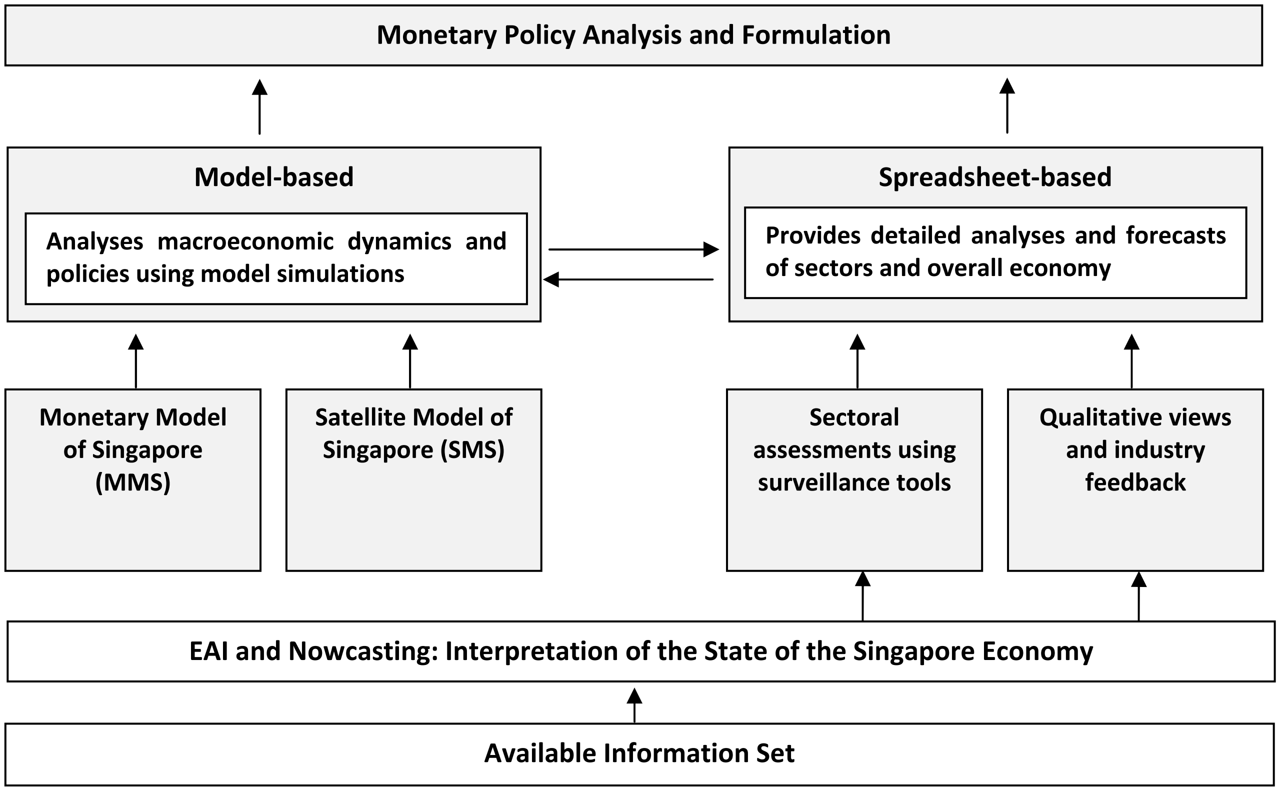
In comparison, the spreadsheet approach focuses on a detailed analysis of current sectoral developments and projections of short-term trends. Apart from monitoring a large number of relevant indicators, the sectoral analysis is supported by qualitative assessments and feedback gathered from industry players, financial institutions and other government agencies. In addition, EPG uses industry-specific tools that serve as valuable inputs to the surveillance and forecasting process. For instance, the Electronics Leading Indicator (ELI) index was developed to help predict the state of the domestic electronics manufacturing industry. Another surveillance tool is EPG's Economic Activity Index (EAI), introduced in the October 2010 *Review*. The EAI is a monthly composite index of coincident economic series, providing useful information on monthly developments within any given quarter.

However, a specific impediment to timely surveillance of the economy has been lags in the collation and publication of essential economic data. In Singapore, the first comprehensive estimate of economic activity, the Gross Domestic Product (GDP), is released at least two to three weeks after the end of every quarter.

In the interim, policy-makers and analysts can look to a steady flow of higher frequency—monthly or weekly—indicators as more timely gauges of current economic conditions. These typically include "hard" data such as industrial production, exports and retail sales, as well as "soft" indicators such as consumer and business surveys, especially the widely monitored Purchasing Managers' Index (PMI). The latter tend to be compiled and released more promptly than the "hard" data, although they only provide snapshots of households' and firms' present situation.

Nevertheless, the use of monthly indicators as a surveillance tool poses two difficulties. First, there is the issue of relating the intra-quarter information in such indicators to the quarterly GDP measure of overall activity. Second, there is a need to deal with the "jagged edge" structure of data flow due to non-synchronous publication lags. From a statistical point of view, a satisfactory solution would have to resolve both of these *mixed frequency* and *missing values* problems for the more up-to-date information in monthly indicators to be efficiently utilised.

Chart 1
Economic Surveillance Framework in EPG, MAS



This Special Feature presents an approach to overcoming these problems that has come to be known as "nowcasting", thus augmenting EPG's suite of macroeconomic surveillance tools. Economic nowcasting should be distinguished from the traditional activity of forecasting. It refers to an assessment of the state of the economy made during the reference quarter, while forecasting refers to an estimate made prior to the quarter.

In the next few sections, two alternative nowcasting models are presented and implemented. Following this, their relative efficacy in providing an early estimate of Singapore's economic performance is evaluated in a pseudo real-time context, and an attempt is made to see whether combining the approaches results in more accurate nowcasts.

Alternative Nowcasting Models

Until recently, the main approach to nowcasting has been based on the econometric estimation of "bridge" equations (Baffigi, Golinelli and Parigi, 2004). As its name suggests, a bridge equation entails the specification of a dynamic relation between changes in quarterly GDP and the corresponding movements in a plethora of monthly time series. Such an approach aims to bridge the gap between the information content of the higher frequency indicators and the delayed (but more complete) national accounts data. Nonetheless, the estimation of bridge equations does not entail the presumption that the relationship between GDP and the monthly indicators is causal or behavioural—the only requirement is that the predictor variables have strong explanatory power. On this basis, a general empirical form is preferred when specifying the bridge equation, as in the autoregressive distributed lag (ARDL) model:

$$\Delta y_t^Q = \mu + \sum_{k=1}^{\ell} \phi_k \Delta y_{t-k}^Q + \sum_{i=1}^{q} \sum_{k=0}^{\ell} \varphi_{ik} \Delta x_{it-k}^Q + \varepsilon_t \quad (1)$$

In this equation, the change in quarterly GDP (Δy_t^Q) is regressed on lags of itself and the contemporaneous and lagged values of a carefully selected set of time-aggregated monthly indicators (Δx_t^Q). In real-time nowcasting, these regressors are obtained using the known monthly values together with projections from Box-Jenkins (or ARIMA) models for data that has yet to be released.

More recently, the related fields of forecasting and nowcasting have been revolutionised by the rediscovery of factor models, which exploit the information in a large number of economic variables for prediction purposes.[1] The second approach employed in this Special Feature for nowcasting the Singapore economy is based on such a model, albeit the more parsimonious variant proposed by Mariano and Murasawa (2003). The point of departure in their approach is the static one-factor model given by:

$$\begin{pmatrix} \Delta y_t^M \\ \Delta x_t^M \end{pmatrix} = \begin{pmatrix} \mu^y \\ \mu^x \end{pmatrix} + \begin{pmatrix} \beta^y \\ \beta^x \end{pmatrix} f_t + \begin{pmatrix} u_t^y \\ u_t^x \end{pmatrix} \quad (2)$$

where y_t^M is a latent variable associated with monthly GDP and x_t^M is a vector of variables observed every month. The common factor driving the co-movements in these variables, f_t, is modelled as an autoregressive process while the idiosyncratic disturbance terms in u_t^y and u_t^x are assumed to be uncorrelated with each other.

If monthly observations of GDP were available, the nowcasting model above reduces to a standard factor model. Hence, known and projected values of the monthly indicators can be used to nowcast current quarter GDP growth. However, in practice, y_t^M is unobservable and only y_t^Q is observed every third month. To circumvent this, Mariano and Murasawa (2003) made use of the following accounting identity linking monthly to quarterly GDP.[2]

$$y_t^Q \equiv \frac{1}{3}\left(y_t^M + y_{t-1}^M + y_{t-2}^M\right) \quad (3)$$

Taking three-period differences of y_t^Q results in:

$$\Delta y_t^Q = \frac{1}{3}\Delta y_t^M + \frac{2}{3}\Delta y_{t-1}^M + \Delta y_{t-2}^M + \frac{2}{3}\Delta y_{t-3}^M + \frac{1}{3}\Delta y_{t-4}^M \quad (4)$$

Substituting the equation for Δy_t^M in (2) into (4) yields the following dynamic factor model:

$$\begin{pmatrix} \Delta y_t^Q \\ \Delta x_t^M \end{pmatrix} = \begin{pmatrix} 3\mu^y \\ \mu^x \end{pmatrix} + \begin{pmatrix} \beta^y \left(\frac{1}{3} f_t + \frac{2}{3} f_{t-1} + f_{t-2} + \frac{2}{3} f_{t-3} + \frac{1}{3} f_{t-4} \right) \\ \beta^x f_t \end{pmatrix} + \begin{pmatrix} \frac{1}{3} u_t^y + \frac{2}{3} u_{t-1}^y + u_{t-2}^y + \frac{2}{3} u_{t-3}^y + \frac{1}{3} u_{t-4}^y \\ u_t^x \end{pmatrix} \quad (5)$$

Unlike (2), this model can be estimated by the Kalman filter using the observed data. Thus, the dynamic factor model provides an elegant solution to the mixed frequency problem, essentially by treating the change in quarterly GDP as distributed lags of the (monthly) common factor and disturbance term. At the same time, the missing values of the monthly indicators can be replaced by forecasts within the dynamic factor framework.

Table 1
Monthly Indicators for Nowcasting

Economic Indicator	Marginal $\bar{R}^2$	Publication Lag	Time Series Model
Index of Industrial Production (IIP)	0.36	26 days	ARIMA(0,1,|1,4|)
Non-Oil Domestic Exports (NODX)	0.04	17 days	ARIMA(1,1,|1,3|)
Food and Beverage Receipts (F&B)	0.10	45 days	ARIMA(1,1,1)
Manufacturing Purchasing Managers' Index (PMI)	0.03	3 days	ARIMA(1,0,0)
Construction Certified Progress Payments (CP)	0.01	31–37 days	ARIMA(1,1,2)

1 See Stock and Watson (2002) and Angelini, Bańbura and Rünstler (2010). An application to forecasting Singapore's economy is found in Chow and Choy (2009).

2 Quarterly GDP is expressed as the average instead of the sum of monthly GDP to make it comparable with the monthly indicators used in the empirical model.

Indicator Selection

In deciding on the monthly indicators (the x_t^M's) to be used in the nowcasting models, three criteria are emphasised: relevance, timeliness and correlation. First, the indicators chosen should be reasonable proxies for the production or sale of some type of goods or services in Singapore; otherwise, there would be no economic rationale for using them to nowcast aggregate output. Applying this criterion produced an initial list of 40 potential indicators covering a wide range of macroeconomic phenomena and economic sectors. They include real activity measures such as industrial production indices, trade aggregates, sales and employment data, as well as survey indicators and financial series.

Second, the requirement of timeliness dictates that delays in releasing the selected indicators should not be so long as to render them useless for nowcasting. Two important series used to compile GDP through the income approach, employment and wages, are therefore ruled out, as both are subject to long publication lags.

The third criterion of strong correlation is implemented in the following way. Initially,pairwise correlation coefficients of the individual indicators with quarterly real GDP are computed. Not surprisingly, "hard" indicators such as non-oil domestic exports and the overall industrial production index rank highly on this score. Accordingly, the quarter-on-quarter changes in these two variables are incorporated into a static regression with the corresponding growth in GDP as the dependent variable and the remaining candidate variables are added, one at a time. The indicator that produces the largest increase in the $\bar{R}^2$ statistic is then selected. This process is repeated until the incremental change in the $\bar{R}^2$ value as a result of adding a further indicator becomes insignificant.

Based on the selection criteria, a total of five monthly indicators are chosen. These are listed in Table 1 together with their marginal explanatory power and publication lags. The number of indicators is deliberately kept low to preserve degrees of freedom and to avoid multicollinearity amongst the chosen indicators.

Estimation of Bridge Equation and Factor Model

The shortest series among the five indicators is the manufacturing PMI, which started from Q1 1999. Consequently, the period from Q1 1999 to Q1 2013 is used to estimate the quarterly bridge equation, making for a total of 57 observations. Seasonal adjustment is performed where necessary and all the data series are transformed into logarithms. The number of lags in the bridge equation is chosen through a general-to-specific procedure, and the final specification is validated by the usual diagnostic tests. The estimated bridge equation is:

$$\Delta y_t^Q = \underset{(-0.36)}{-0.03} + \underset{(1.32)}{0.07}\,\Delta y_{t-1}^Q + \underset{(14.5)}{0.25}\,\Delta IIP_t^Q + \underset{(3.92)}{0.11}\,\Delta NODX_t^Q$$
$$+ \underset{(0.44)}{0.01}\,PMI_t^Q + \underset{(5.28)}{0.14}\,\Delta F\&B_t^Q + \underset{(2.36)}{0.05}\,\Delta CP_t^Q$$
$$\bar{R}^2 = 0.89 \quad S.E. = 0.008 \quad DW = 1.88$$

In this equation, the industrial production index and non-oil domestic exports are both statistically significant, as seen from the *t*-statistics shown in parentheses. This may help to explain why the PMI is not, as all three series tend to be highly correlated. Of the remaining variables, food and beverage receipts appear to capture services output well, while certified payments is an obvious proxy for construction activity. Overall, the selected variables have good explanatory power for GDP growth, as shown by the very high $\bar{R}^2$ value.

The dynamic factor model in Equation (5) is estimated for the same sample period from Q1 1999 to Q1 2013 by including the five monthly variables in the vector x_t^M, together with y_t^Q, the quarterly GDP series. The Akaike Information Criteria (AIC) is used to select an optimal lag length of two for the dynamic factor structure. In the estimated factor model, the loading coefficients ($\hat{\beta}^y$ and $\hat{\beta}^x$) have the right signs and are mostly significant.

Model Comparison and Combination

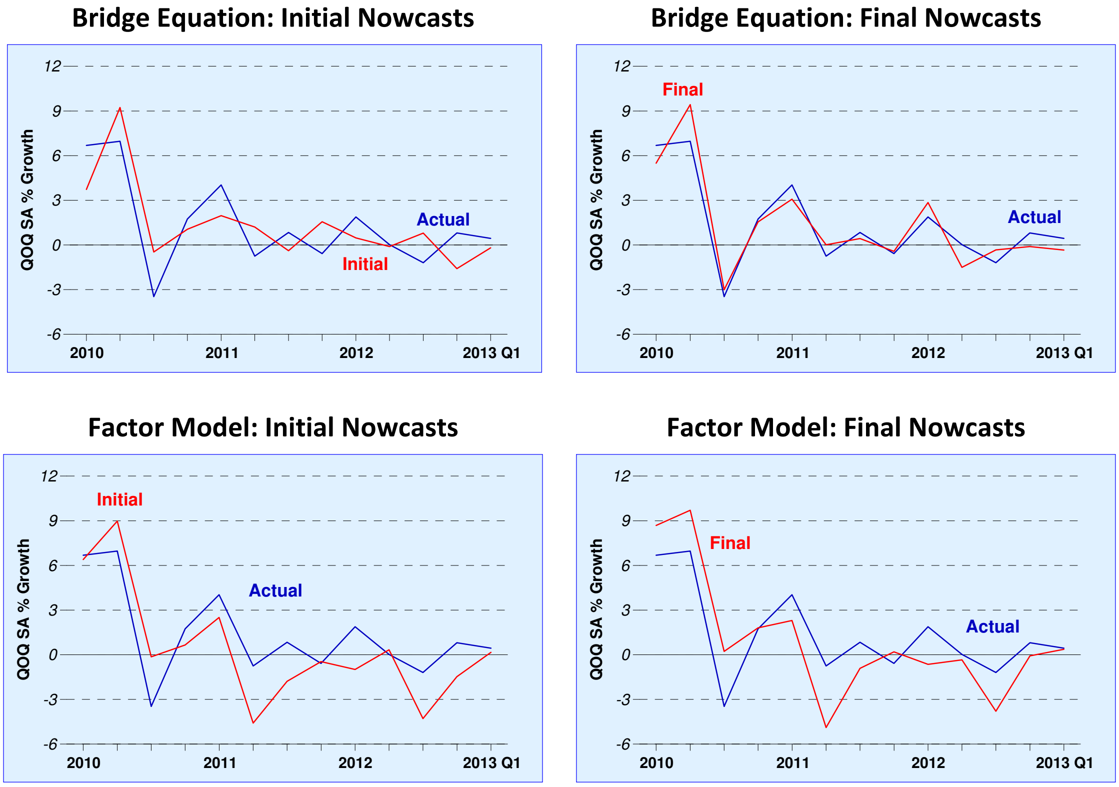
In this section, the two alternative approaches to nowcasting Singapore's current quarter-on-quarter GDP growth, namely, the bridge equation and the dynamic factor model, are compared. To this end, both models are estimated over a shorter sample period from Q1 1999 – Q4 2009, and nowcasts are generated over the period Q1 2010 – Q1 2013. The real-time context of nowcasting is replicated by re-estimating the models recursively at each quarter using the latest available data. However, the functional form of the bridge equation is kept unchanged and two autoregressive lags are maintained in the factor model.

As mentioned earlier, missing values of the monthly indicators within a quarter need to be filled in by forecasts before estimating the bridge equation. The time series models employed for this purpose are reported in Table 1. These are relatively low-order ARIMA models fitted to the logarithms of the respective series. In the case of the factor model, the unknown observations are automatically replaced by projections.

For each quarter, two sets of nowcasts are generated. The first is produced towards the end of the second month in the reference quarter, when one month's information on three of the indicators, viz., industrial production, exports and PMI, become available. This is referred to as the 'initial' nowcast. The second nowcast, made at the end of the quarter, adds one month of data for the food and beverage index and certified payments, as well as a second month of observations on the other series. This is referred to as the 'final' nowcast. In total, 26 pseudo-nowcasts of Singapore's quarterly GDP growth are generated from each model, with one-half of them coming from the initial round and the other half from the final cycle.

These point nowcasts are plotted in Chart 2 alongside the actual GDP outcomes. Several conclusions emerge from comparing the initial and final nowcasts generated by the bridge and factor models.

Chart 2
Real-time Performance of Nowcasting Models, Q1 2010 – Q1 2013



First, it is evident that both approaches produce less precise *ex ante* initial nowcasts of GDP growth, when the information set is limited to a single month of data. Second, the initial nowcasts from the bridge equation are more accurate in terms of being closer to observed outturns, while the factor model tends to underestimate actual quarterly GDP growth. Nonetheless, the latter generally produces more reliable predictions of the *directional changes* in Singapore's real GDP growth from one quarter to the next, suggesting that the factor model may be better at detecting turning points in the business cycle.

Third, the bridge equation also performs better than the factor model with respect to the final nowcasts. Indeed, the out-of-sample nowcasts from the model are able to track the pattern of rather volatile gyrations in GDP growth, except for the most recent period. Table 2 reports the root mean squared errors (RMSEs) of the initial and final nowcasts. At just over 1%, the RMSE of the bridge equation is less than half that of the factor model, and is also relatively small when compared to the mean variation in quarterly GDP growth, which is about 3%.

In addition, the reduction in RMSE obtained by moving from the initial to the final nowcasts in the bridge equation is of an order of magnitude around one percentage point. This represents a substantial improvement and suggests that the information content in the second month of any given quarter is crucial for the accuracy of the nowcasts.

Following the forecasting literature, a combination of nowcasts from the bridge equation and factor model is also created by taking their simple average.[3] This procedure generates a sequence of predictions which performs better in the initial nowcasting stage than the two underlying approaches, as shown in Table 2. However, the combination strategy is not able to improve on the bridge equation with regard to the final nowcasts, suggesting that the bridge equation summarises well the information in the high frequency indicators.

In sum, the bridge equation and dynamic factor model can be jointly used to generate combination nowcasts at the earlier stage when only one month of data is available. When an additional month of data is available, the nowcasts from the bridge equation are more reliable.

Table 2
Comparison of Nowcast Accuracy* (%)

Model	Initial	Final
Bridge	1.95	1.07
Factor	2.21	2.21
Combination	1.70	1.26

* Figures are the average root mean squared errors in percent.

Sum-up

This Special Feature shows that nowcasting models can be a valuable tool to help guide economic policy-makers and analysts to an informed view of the current state of the economy. The five monthly economic variables selected for the pseudo real-time nowcasting exercises are found to contain useful cyclical information on current growth in Singapore, by virtue of either their robust correlation with aggregate activity, or their spillover effects on the broader economy. Hence, the two nowcasting models can be utilised on their own, or in combination, to produce quantitative GDP growth projections on a timely basis, pending the release of official data. Such efforts will further add to and enhance EPG's economic surveillance and forecasting toolkit, and form part of our pluralistic approach towards monetary policy analysis and formulation.

3 A weighted average using the models' respective RMSEs as weights did not produce qualitatively different results.

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