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Analyzing and Forecasting Business Cycles in a Small Open Economy: A Dynamic Factor Model for Singapore

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Abstract

A dynamic factor model is applied to a large panel dataset of Singapore's macroeconomic variables and global economic indicators with the initial objective of analyzing business cycles in a small open economy. The empirical results suggest that four common factors are present in the quarterly time series, which can broadly be interpreted as world, regional, electronics and domestic economic cycles. The estimated factor model explains well the observed fluctuations in real economic activity and price inflation, leading us to use it in forecasting Singapore's business cycles. We find that the forecasts generated by the factors are generally more accurate than the predictions of univariate models and vector autoregressions that employ leading indicators.

Key Words: Business cycle, Dynamic factor model, Forecasting, Singapore

JEL Classification: C32, C33, E32, E37

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1 Introduction

The analysis of business cycles in small and open economies has always presented the empirical researcher with particular challenges. A fundamental reason for this lies in the vulnerability of such economies to the vagaries of international macroeconomic fluctuations, which accentuate the intrinsic volatility caused by domestically generated disturbances. Nonetheless, many papers appearing in scholarly journals are cognizant of the role played by international fluctuations when documenting the stylized facts of business cycle co-movements in relatively open economies such as Sweden, Switzerland, New Zealand and Korea (see respectively Englund *et al*., 1992; Danthine and Girardin, 1989; Kim *et al*., 1994; Kim and Choi, 1997). In addition to these industrialized country studies, Kose, Otrok and Whiteman (2003) successfully used worldwide, regional and country-specific business cycles to explain the aggregate co-movements observed in a broad cross-section of countries.

Two articles that examined the nature of economic fluctuations in the small and newly industrialized economies of Hong Kong and Singapore find that, in line with the studies cited above, external factors contribute significantly to their internal gyrations (Leung and Suen, 2001; Choy, 2009). Unfortunately, attempts to include the impact of international events in business cycle modelling of highly open economies are often hampered by the need for parsimony. Typically, the problem is approached on an ad hoc basis, using only a limited number of foreign variables to represent external shocks to the economy. This is to avoid running into the degrees-of-freedom problem associated with a loss of efficiency in regression-type models such as single equations, large scale macroeconometric models and vector autoregressions.

As a remedy, one could consider dynamic factor models that permit the incorporation of a large number of variables capturing the foreign disturbances which buffet small and open economies as well as impulses originating from domestic sources. This class of models is appealing from a theoretical standpoint since it views all macroeconomic fluctuations as being driven by a small number of common shocks and an idiosyncratic component that is peculiar to each economic time series—an idea that was already implicit in Burns and Mitchell's (1946) early characterization of business cycles. In spite of the seminal papers by Sargent and Sims (1977) and Stock and Watson

(1989), dynamic factor models have only lately been revived for the purpose of forecasting real economic activity and inflation in the US and larger European countries (see, *inter alia*, García-Ferrer and Poncela, 2002; Stock and Watson, 2002b; Forni *et al*., 2003; Artis *et al*., 2005; Schumacher, 2007). However, their use as a tool of business cycle analysis particularly with respect to small open economies remains relatively unexplored, even as the statistical techniques and computing power needed to efficiently exploit the vast amount of information in large panel datasets were developed.

In this paper, we demonstrate the usefulness of a dynamic factor model for the analysis and prediction of business cycles in an archetypal small open economy with an empirical application to Singapore. Unlike the earlier work on single factor models by Stock and Watson (1989) and others aimed at the construction of composite indexes of economic activity based on a mere handful of coincident indicators, we utilize a large collection of 177 quarterly time series that includes foreign economic indicators as well as domestic variables to extract the unobserved factors responsible for macroeconomic fluctuations. Another difference is that we allow more than one common factor to drive fluctuations, which is congruent with the assumption that business cycles are caused by multiple sources of shocks. Moreover, the number of shocks is determined rigorously using the recent method proposed by Bai and Ng (2007).

It turns out that the bulk of the observed co-variation in the variables under consideration can be explained with just four common factors, suggesting that the Singapore macroeconomic data can be approximated by a low-dimensional factor structure despite its diversity. Although we refrain from imposing identification assumptions, we surmise that the factors represent world, regional, electronics and domestic economic cycles through a detailed analysis of their explanatory power for various time series. Since the estimated factors account very well for the cyclical fluctuations in real economic activity and general price inflation, we use them next in short-term forecasting. We generate predictions recursively from a direct multistep forecasting methodology and compare them with forecasts of univariate and multivariate time series models. The latter makes use of known leading indicators of the Singapore economy and could be considered to be a sophisticated competitor to factor models. We find that the factor approach leads to improvements in forecast performance for most of the variables investigated.

The rest of the paper is structured as follows. Section 2 presents the dynamic factor model for the Singapore economy, describes its estimation, and outlines the Bai-Ng test for the number of aggregate shocks in the model. Section 3 describes the panel dataset employed and its cyclical properties. Section 4 reports the empirical results from estimating the dynamic factor model and provides plausible interpretations of the latent factors by relating them to macroeconomic variables. In Section 5, we produce pseudo out-of-sample predictions of the growth rates in major output and price indicators from the alternative forecasting models and formally evaluate their relative accuracy. Lastly, the paper's conclusions are given in Section 6.

2 The Dynamic Factor Model

2.1 Representation and estimation

Variables cast in a factor analytic representation are characterized by the sum of two mutually orthogonal and unobservable components: the common component driven by a small number of factors and the idiosyncratic component driven by variable-specific shocks. Denoting the size of the cross-sectional panel by N and the length of each time series by T, let $X_t, t = 1,\ldots,T,$ be the N-dimensional vector of stationary time series. The dynamic factor model for these variables is given by:

$$X_{it} = \lambda_i(L) f_t + \varepsilon_{it} \tag{1}$$

for $i = 1,\ldots,N.$ The $q \times 1$ vector f_t contains the common factors and $\lambda_i(L) = \lambda_{i0} + \lambda_{i1}L + \cdots + \lambda_{is}L^s$ is an s-th order polynomial in the lag operator L that represents a vector of dynamic factor loadings. In contrast to the exact factor model, the idiosyncratic disturbance ε_{it} is permitted to have limited serial and cross-correlation (see Forni *et al.*, 2000 and Stock and Watson, 2002b). However, the factors and idiosyncratic errors are assumed to be mutually uncorrelated at all leads and lags—an assumption that is essential for estimation of the factor model.

The central idea of the factor model as applied to business cycle analysis is that information in a large dataset can be parsimoniously summarized by a small number of latent factors i.e. $q \ll N$, each of which could be estimated as a weighted linear combination of the cycles found in individual variables. In other words, economic variables are pooled to average out noisy disturbances in the idiosyncratic component and to extract the cyclical signals in the common component. We assume that the latter explains the major part of the variation in observed time series regardless of the cross-sectional dimension. In the dynamic version of the factor analytic model described by (1), current realizations of variables can be affected by the past values of factors through a finite distributed lag structure. Further, the dynamic factor model relaxes the assumption of uncorrelated disturbances required in classical factor analysis by allowing for both contemporaneous and lagged correlation between the idiosyncratic terms, thereby accommodating the typical statistical features of macroeconomic data employed in business cycle analysis and forecasting applications.

For estimation purposes, the model in (1) often reformulated as:

$$X_t = \Lambda F_t + \varepsilon_t \tag{2}$$

where $F_t = \left(f_t', \ldots, f_{t-s}' \right)'$ is an $r = q\left(s+1\right)$-dimensional vector of stacked common factors and Λ is now an $N \times r$ matrix of factor loadings. Notice that the r static factors in F_t consist of current and s lagged values of the q dynamic factors in f_t. The key advantage of this static representation is that principal components analysis can be applied to extract the common factors from a huge panel of related time series in a computationally convenient manner. Specifically, the column space spanned by the dynamic factors can be estimated consistently as $N,T \to \infty$ jointly by taking principal components of the covariance matrix of X_t, provided mild regularity conditions are satisfied (Stock and

Watson, 2002b).[3] One key condition is that the static factors included in the model has to be at least equal to their true number, so it is important that a reliable procedure be used to determine the value of r.

2.2 Determination of the number of factors

Bai and Ng (2007) demonstrated that the dynamic factor in (1) always has the static factor representation (2) in which the dynamics of F_t are characterized by a VAR. In the same paper, they showed how the number of dynamic factors, q, can be inferred from a knowledge of the number of static factors, r. Since some factors in the static model are dynamically dependent—being lags of the others—it follows that $q \le r$. This observation forms the basis of Bai and Ng's method to determine the value of q, which the authors interpret as a test for the number of primitive shocks driving macroeconomic fluctuations. Specifically, q is the reduced rank of the residual covariance matrix for the static factor VAR, or the number of non-zero eigenvalues associated with it.

The Bai-Ng procedure consists of two steps. In the first, the static factors are estimated by principal components analysis and r is consistently selected using one of the six variants of information criteria developed in their earlier work (Bai and Ng, 2002). All the criteria are asymptotically equivalent but their small sample properties vary due to different specifications of the penalty term. The most widely used criterion and one of the best in terms of performance in simulations is the following:

$$IC(r) = \ln\left(V\left(r,F\right)\right) + r\left(\frac{N+T}{NT}\right)\ln\left(\min\left\{N,T\right\}\right) \tag{3}$$

$$V\left(r,F\right) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(X_{it} - \Lambda_i F_t\right)^2 \tag{4}$$

The penalty imposed by the second term in (3), which is an increasing function of N and T as well as the number of factors, serves to counter-balance the minimized residual sum of

[3] Stock and Watson (2002a) in fact proved the stronger result that, even if there is parameter instability caused by, say, structural change, the principal component estimates are still consistent because their precision improves with N, thus making it possible to compensate for short panels where T is relatively small.

squares by effecting an optimal trade-off between goodness of fit and over-fitting. Evidently, the criterion can be viewed as an extension of the Akaike information criterion (AIC) with consideration for the additional cross-sectional dimension to the time series.

In the second step, the principal components estimates of the factors conditional on the value of r selected are used to fit a VAR model of order p and the least squares residuals are obtained. As mentioned above, the method to determine q is based on the estimated eigenvalues of the residual covariance matrix. Let these be denoted as $\hat{c}_1 \geq \hat{c}_2 \geq \ldots \geq \hat{c}_r \geq 0$ in descending order. The cumulative contribution of the k-th eigenvalue is given by:

$$\hat{D}_k = \left(\frac{\sum_{j=k+1}^{r} \hat{c}_j^2}{\sum_{j=1}^{r} \hat{c}_j^2} \right)^{\frac{1}{2}} \tag{5}$$

Assuming that the true number of dynamic factors is q, $c_k = 0$ for $k > q$. Bai and Ng (2007) showed that $\hat{D}_k$ converges asymptotically to zero for $k \geq q$ at a rate depending on the sampling error induced by estimation of the VAR covariance matrix. Hence, for non-negative m and $0 < \delta < 1/2$, the smallest integer k that satisfies the bounded set $\left\{ k : \hat{D}_k < m / \min\left[N^{\frac{1}{2}-\delta}, T^{\frac{1}{2}-\delta} \right] \right\}$ is the estimated number of dynamic factors in the model. The large sample property of the test ensures that this value of k will be a consistent estimate of q as N and T diverge.

3 The Panel Dataset

Singapore has a large and reliable database of macroeconomic variables by the standards of newly industrialized economies. The national income accounts, in particular, are very rich in revealing the industry details of the compilation of real GDP by the production approach. Given this, we broaden our search for the set of cyclical indicators to be included in the factor model to time series of the quarterly frequency, hence providing a more comprehensive coverage of the many facets of macroeconomic activity. Needless to say, monthly data is not excluded from the exercise, although these have to be aggregated or averaged to yield quarterly values. The variables selected are listed in the appendix.

As our interest is in analyzing and predicting Singapore's growth cycles, almost all the variables we work with are transformed into approximate year-on-year (or annualized) growth rates by taking the fourth differences of their logarithms. In this respect, we depart from the conventional practice of modelling period-on-period (or quarterly) growth rates since these are very volatile for a small open economy like Singapore. The only variables to which the growth rate transformation is not applied and where seasonally adjusted data are used instead are interest rates, exchange rates, unemployment and business expectations series.

To avoid overweighting any one series, all raw and transformed variables are normalized by subtracting their means and dividing by their standard deviations. A visual inspection of time plots revealed a handful of unusual occurrences during the sample period from 1993Q1 to 2008Q2 due to the Asian financial crisis of 1997 and the outbreak of the SARS disease in early 2003. As a robustness measure, the outlying observations are excluded in the computation of the means and standard deviations of contaminated series. In view of the fact that Singapore is a major producer of semiconductor products, the choice of starting date was dictated by the availability of data on electronics time series, resulting in $T = 62$. However, the relatively small sample size is compensated by a large panel that consists of 41 transnational and 136 national indicators, making $N = 177$. These series can be loosely grouped as follows:

- Real GDPs of Singapore's major trading partners and their weighted average (10 countries and one region); composite leading indexes of the US and major European and Asian economies; foreign stock prices and interest rates

- Global semiconductor sales, US technology cycle index and electronics leading indicators plus index; world oil price, non-fuel commodity prices and global consumer prices

- Singapore’s real GDP and expenditure components; gross value-added output in the manufacturing, service and construction sectors

- Industrial production indices; investment commitments and business expectations surveys; composite leading index

- Construction and housing related series e.g. residential investment, building contracts awarded and property prices

- Sectoral indicators such as retail sales, new car registrations, tourist arrivals, air and sea cargo handled, electricity generation and company formations in different sectors

- Foreign trade series: exports and imports of goods and services, domestic exports and re-exports disaggregated into oil and non-oil categories

- Export and import price indices; terms of trade; consumer and producer price indices; GDP and sectoral deflators

- Labour market variables: changes in employment, retrenchments, unemployment rates, unit labour and business costs

- Financial series such as stock prices, interest rates and exchange rates; monetary aggregates and bank credit

As noted above, the importance of international and foreign economic indicators for short-term monitoring of the Singapore economy should not be underestimated, so it is imperative to consider external series that are known to co-move with—and sometimes lead—local variables. The time series proven to be leading indicators of business cycles in Singapore are not limited to foreign composite leading indexes and asset prices, but include worldwide electronics indicators such as the book-to-bill ratio for semiconductor equipment, US new orders of electronics and the electronics leading index created by Chow and Choy (2006), which has shown an ability to forecast the global semiconductor cycle up to six months ahead.

The cyclical properties of the domestic variables are also worth highlighting. Almost all of them exhibit procyclical or counter-cyclical movements with reference to the growth cycles in real GDP extracted by a band-pass filter (Choy, 2009). The demonstrably leading series are business anticipations, company formations, producer prices, money supply, the nominal exchange rate and the value of construction contracts awarded (see Chow, 1993 and Chow and Choy, 1995). Some of these indicators are components of the composite leading index compiled by the Singapore authorities (Department of Statistics, 2004), which is also included in the dataset.

By contrast, the consumer price level, nominal wages and interest rates lag economic activity, as do employment and the unemployment rate (Choy, 2009). Finally, the strongly coincident variables are real GDP, sectoral value-added indicators, industrial production, non-oil domestic exports, retail sales and electricity generation. Regardless of a variable's cyclical timing classification, it can easily be fitted into the very flexible factor framework by virtue of the lag polynomial in (1). As a result, the inclusion of leading, coincident and lagging economic indicators in the estimation and forecasting exercises promises to deliver sharper estimates of the latent factors underlying movements in Singapore's output and prices.

4 Analyzing Singapore Business Cycles

Implementing the Bai-Ng information criterion in (3) and (4) on our panel dataset with a pre-specified upper bound of 16 on r suggests that around 10 factors should be included in the static model. Next, a first order VAR model selected by the Bayesian information criterion (BIC) was fitted to the factors estimated by principal components in the first step. The eigenvalues of the residual covariance matrix were then computed and the test statistic in (5) constructed. Based on the settings of $m = 2.25$ and $\delta = 0.1$ in Bai and Ng (2007), the eigenvalue test picked $q = 4$ dynamic factors for the Singapore data, with the first four factors explaining on average 27%, 14%, 9% and 7% of the total variance in our economic time series, amounting to a cumulative proportion of 57%.[4] This is remarkable in view of the large number and diversity of the variables included in the analysis. By contrast, the fifth and sixth factors account for only 6% and 4% respectively, whilst they are also less amenable to economic interpretation.

In attempting to assign interpretations to the factors, we are aware of the pitfalls involved. The factor model suffers from a lack of identification because the estimated factors are just linear combinations of the primitive shocks underlying business cycles. Nevertheless, we follow Stock and Watson (2002b) and regress every variable in the dataset against each factor to see if a particular factor is strongly related to a specific group of macroeconomic variables. The R^2, or explanatory power, of the first four factors for individual series are graphed as bar charts in Figures 1–4, where the numbers on the horizontal axis refer to variables (see the appendix listing) and the vertical lines divide them into the ten groupings of the previous section.

The first factor reflects the general business cycle in Singapore and places heavy weights on regional economic series, domestic production, employment and exports. In terms of sectoral breakdown, manufacturing, commerce and financial services are strongly emphasized. This is very much in line with the regional hub status of Singapore and her role as an exporter of high value-added parts and accessories in the electronics supply chain based in Asia. By contrast, the second dynamic factor clearly picks out the indicators associated with the local construction cycle and supporting services such as real estate transactions and bank lending. Labour market variables and effective exchange rates also load highly on this component.

As we move to the other two factors, the heights of the bars in the graphs diminish noticeably, testifying to their lower explanatory power. The third estimated factor seems to be linked to the global tech cycle, the indigenous semiconductor industries and the transportation sector. Domestic interest rates also figure prominently in this factor. The fourth factor emphasizes nominal price series, especially the producer price index, trade price indices, the oil price, and other world prices. Reflecting the openness of Singapore, this factor primarily captures the external price shocks hitting the economy. As Abeysinghe and Choy (2009) have shown, oil price hikes and foreign price increases are

[4] These figures are derived from the trace R^2 statistic for the estimated factor model.

initially passed through to import costs and then onto producer and consumer prices. In the light of these findings, we broadly interpret the driving forces behind short-term macroeconomic fluctuations in Singapore as regional business cycles, domestic disturbances, electronics cycles and world price shocks.

Figure 1 R^2 **values for first factor**

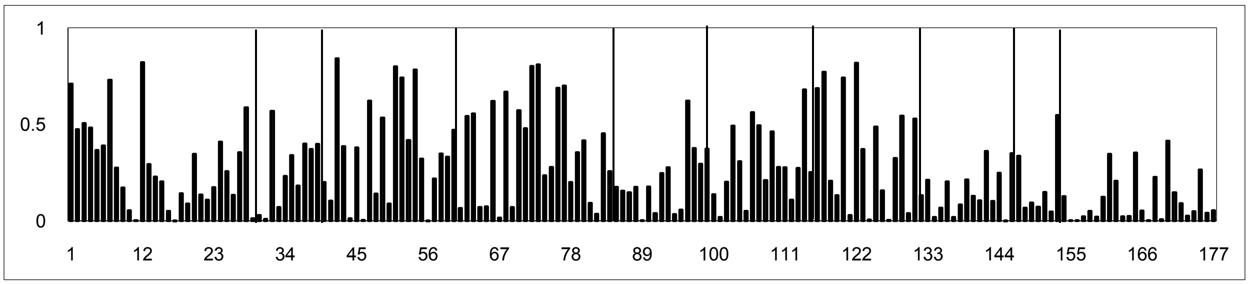

Figure 2 R^2 **values for second factor**

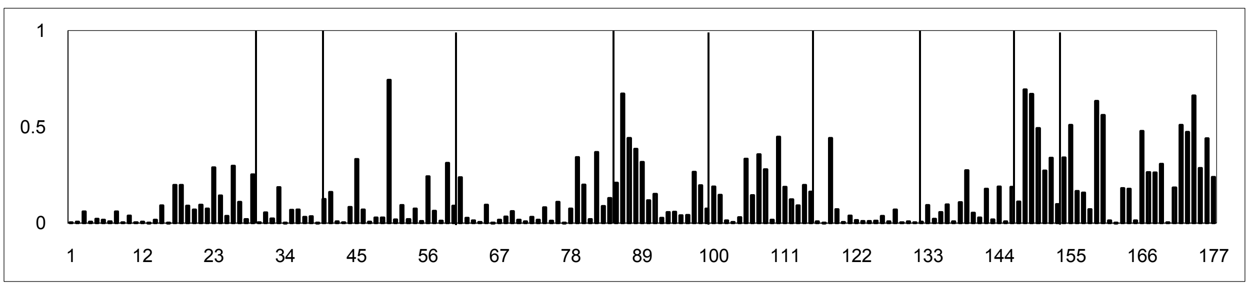

Figure 3 R^2 **values for third factor**

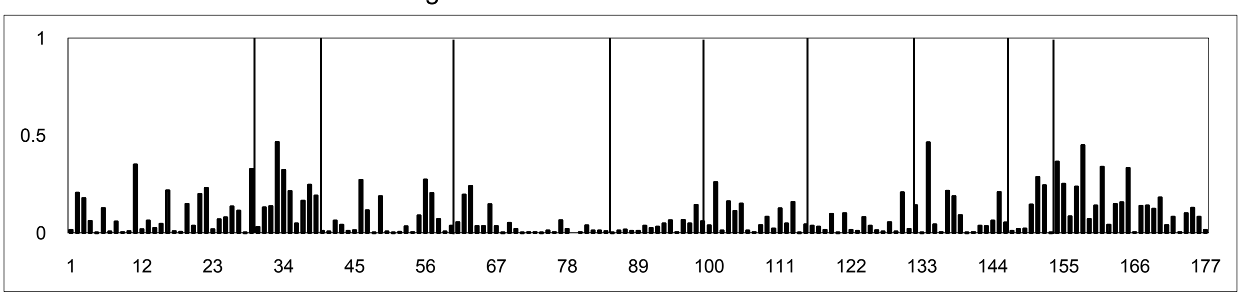

Figure 4 R^2 **values for fourth factor**

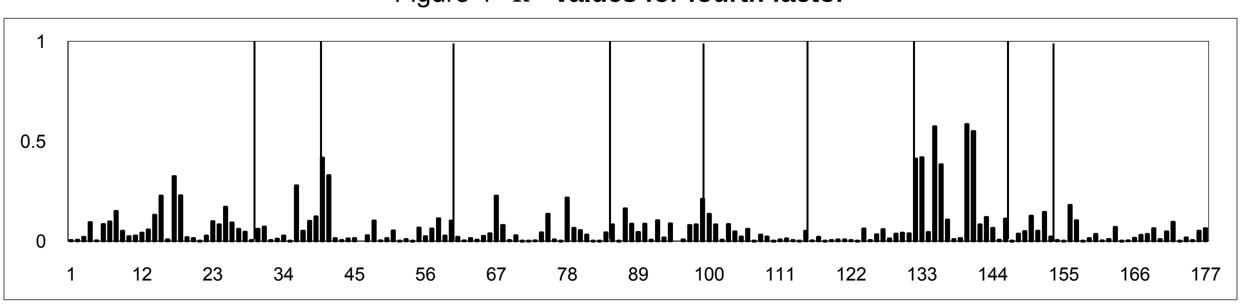

Table 1 **Sectoral explanatory power of common factors**

Variable	Factor 1	Factor 2	Factor 3	Factor 4	All
Real GDP	0.84	0.01	0.06	0.01	0.92
Manufacturing*	0.53	0.03	0.19	0.00	0.75
Electronics	0.56	0.01	0.24	0.01	0.82
Chemicals	0.07	0.00	0.03	0.00	0.11
Biomedicals	0.07	0.09	0.03	0.02	0.22
Services	0.80	0.02	0.00	0.05	0.87
Commerce	0.78	0.07	0.00	0.00	0.86
Transport & communications	0.22	0.06	0.20	0.06	0.54
Financial & business services	0.47	0.09	0.03	0.10	0.69
Construction	0.09	0.74	0.01	0.01	0.85

* Manufacturing is a measure of value-added while the industry breakdown is based on production.

Since the dynamic factor model does a good job of explaining aggregative cycles, it is interesting to see if it can also account for disaggregate sectoral fluctuations. With regard to this, the relative importance of aggregate and sectoral shocks in the genesis of business cycles has long been a subject of debate. In theory, real business cycle models such as the prototype developed by Long and Plosser (1983) show that independently distributed sectoral disturbances can be a source of fluctuations. However, empirical analyses by Norrbin and Schlagenhauf (1991) and Caporale (1997) found the common factor to be more influential than industry-specific factors in practice.

Here, we provide some evidence on this issue in the context of the Singapore economy by regressing the normalized growth rates of selected output series on the estimated factors, one at a time and simultaneously. We shall consider the gross value-added of the major economic sectors of manufacturing, services, and construction, sub-sectors within them, and industrial production indices. A high value of R^2 in a regression indicates that a factor (or factors) explains well the dependent variable. Table 1 contains the results. As expected, the first dynamic factor proves to be the most important for explaining economic performance at the aggregate level and across the various sectors. The second factor accounts for the bulk of the variance in construction value-added while the third turns out to be a good predictor of electronics output in Singapore, consistent with their interpretations given above. Being associated with foreign price shocks, the last factor understandably plays a negligible role in driving sectoral fluctuations.

Turning to the final column in Table 1, we see that the common factors jointly explain more than half of the growth cycle fluctuations in individual sectors and industries, except in the cases of chemical and biomedical production.[5] The latter industry tends to be very unpredictable due to changing product mixes and drug approval delays, so its low commonality is not surprising. By contrast, the R^2 values of the regressions for real GDP, services and construction are 0.92, 0.87 and 0.85 respectively. Such high coefficients of determination suggest that the dynamic factor model provides an excellent in-sample fit to real variables. In addition, the empirical factors also explain 59% of the variation in CPI inflation. The estimated factor model is therefore potentially useful for forecasting, as we will find out in the next section.

The regression results also confirm the presence of interdependencies between economic sectors and a high degree of co-movement amongst sectoral outputs in Singapore—a key stylized fact of business cycles. Furthermore, with reference to the interpretation of the factors, it appears that aggregate shocks originating from abroad are the predominant causes of the economy's cyclical motions. Disaggregate disturbances are largely limited to boom-bust cycles in the domestic building sector and idiosyncratic factors in the petrochemical and pharmaceutical industries.

5 Forecasting with the Factor Model

We employ a common framework for generating pseudo out-of-sample forecasts from the dynamic factor and other models. Initially, each forecasting model described below is estimated using observations over the period 1993Q1 to 2004Q4 and its h-step ahead predictions calculated for $h = 1, \ldots, 4$ quarters (given the volatility of Singapore's economic growth, we eschew longer forecast horizons).[6] Thereafter, the sample is augmented by one quarter, the dynamic factors are recomputed, the model is respecified, its parameters reestimated and the corresponding h-step predictions generated by moving the forecast window forward. This recursive procedure is carried on until the sample's end date reaches 2007Q2, at which point the final set of forecasts are made,

[5] In the factor literature, the R^2 values in the last column are known as the degree of commonality, or the fraction of the variance in a time series attributable to the common component of the factor model.
[6] We could not start forecasting earlier due to the relatively short sample length.

resulting in a combined total of 44 out-of-sample predictions for each of the five variables of interest viz., real GDP, manufacturing, services and construction value-added, and consumer price inflation.

5.1 Forecasting models

A distinctive feature of the recent work on forecasting with factor models lies in the way multiperiod predictions are produced. Let the variable to be forecasted be denoted as X_{it} and the four common factors identified in the last section as $\hat{f}_t$. Then an h-step ahead forecast could be computed directly by projecting $X_{i,t+h}$ onto its observable past and the extracted factors as follows:

$$X_{i,t+h} = \mu_h + \alpha_h(L)X_{it} + \beta_h(L)\hat{f}_t + e_{t+h} \qquad (6)$$

At each prediction horizon, a separate forecasting equation is estimated by ordinary least squares and the uniform order of the lag polynomials for the autoregressive component and the factors is determined by minimizing the BIC, starting with a maximum of 6 lags. In simulated real-time forecasting, Stock and Watson (2002b) found that the Bayesian criterion performs satisfactorily when used to select the optimal number of factors and their lags to be included in the forecasting equation.

The direct multistep forecasting methodology prescribed by (6) differs from the usual approach whereby future predictions are generated dynamically by repeatedly iterating the one-step ahead forecasting model and replacing unknown values by their forecasts. The benefit of the direct method is that it obviates the need to model the evolution of the unobserved factors. Furthermore, any misspecification of the one-step ahead model will not be transmitted to the longer forecast horizons since distinct models are estimated at each step of prediction. On the other hand, multistep forecasting entails the estimation of a large number of model parameters, thus reducing efficiency. Despite this trade-off between bias and efficiency, Stock and Watson (2002b) and Boivin and Ng (2005) concluded that the direct approach works well with factor models.

On leaving the dynamic factors out of (6), we get univariate autoregressions for each output and price variable. This constitutes the benchmark models with which the performances of the factor forecasting models are compared. We pick the lag length of the autoregressions through the BIC, with most of the AR models selected being of order 5 or 6, hence allowing complex roots to capture the cyclical behaviour of the data. Such models are therefore not as naïve as they might seem to be. However, it should be noted that the predictions from the AR models are generated iteratively rather than directly, as this is what is usually done in practice.

The multivariate competitor to the foregoing models which we employ in the forecast comparison is a vector autoregression that incorporates leading indicators. As written out below, this model combines the rich dynamics of small-scale VARs with the advantages of the leading indicator approach to forecasting:

$$Y_t = \tau + \Gamma_1 Y_{t-1} + \cdots + \Gamma_p Y_{t-p} + \eta_t \tag{7}$$

where $Y_t = \left[X_{it}, Z_t\right]'$, Z_t is a vector of macroeconomic and leading variables, Γ_i are lag coefficient matrices and η_t is multivariate white noise. Again, the optimal lag length is determined by the BIC, subject to $1 \le p \le 6$. Once the VAR model has been estimated by least squares, predictions at the various horizons are computed simply by iterating it h steps forward.

The vector of stationary time series in (7) is always a subset of the full dataset employed in the factor analysis, but it changes with the variable being forecasted. When attempting to predict aggregate output growth, it is $y_t = \left[GDP_t, FGDP_t, CLI_t, ELI_t, NEER_t, CA_t\right]'$, where $FORGDP_t$ is a weighted average of incomes in Singapore's major trading partners, CLI_t is the composite leading index, ELI_t is the electronics leading index, $NEER_t$ is the nominal effective exchange rate and CA_t represents total construction contracts awarded—a leading series for the building industry. For manufacturing and service sector growth, GDP_t is replaced by either manufacturing or service value-added output and CA_t is dropped. A priori reasoning hints, and practical experimentation confirms, that foreign income and the leading indexes are not useful predictors of Singapore's construction sector. Consequently, the vector of macroeconomic variables for forecasting the construction growth rate is $y_t = \left[CONSTR_t, CA_t, PPIRES_t\right]'$, the last entry representing the residential property price index.

In predicting price inflation, the endogenous vector is modified to $y_t = \left[CPI_t, GDP_t, OIL_t, WORLDCPI_t, NEER_t\right]'$, in which the crude oil price and the foreign price index serve as leading indicators of inflation. The $NEER_t$ variable is retained since an effective exchange rate appreciation will mitigate imported sources of inflation while GDP growth acts as a proxy for domestic inflationary pressures. This VAR model's predictive power will provide an instructive comparison with the dynamic factor model, where the last included factor represents world price cycles.

5.2 Forecast comparison

The results of the pseudo out-of-sample forecasting exercises are shown in Table 2 in the form of relative root mean square error (RMSE) measures. These statistics are appropriate measures of the models' predictive accuracy under the assumption of quadratic forecast loss functions. The models in competition can be ranked in this order: the dynamic factor model performs best overall, followed by the autoregressive model, then the small-scale VAR.

That the factor model excelled over the other two approaches is not unexpected in view of its ability to track the business cycle movements of the key macroeconomic variables examined in the previous section. But the results for the leading indicator VAR models are rather disappointing as these models are widely used in practical forecasting and have been found to match the accuracy of large-scale macroeconometric models. One possible reason for their inferior performance could be a problem of over-parameterization, aggravated by the limited degrees of freedom offered by our sample.

Conversely, the parsimony inherent in the dynamic factor model is manifested in their good forecast performance. The gains in predictive accuracy over the AR and VAR models are apparent at the 1 to 3 quarters horizons for real GDP and services output growth. In the cases of construction value-added and CPI inflation, the factor model outperformed the other models at all prediction horizons, confirming that the cyclical information summarized by the set of common factors is more comprehensive than that found in individual macroeconomic variables. However, neither the factor nor the VAR model could beat the benchmark autoregressive predictions in the case of manufacturing growth. This finding has been pre-empted by the weaker explanatory power of the empirical factors for the manufacturing sector and its constituent industries.

Of course, some of the observed differences between the RMSEs could just be attributed to chance. Table 3 assesses the influence of sampling variability on the prediction errors by presenting the Diebold-Mariano (1995) test statistics for the null hypothesis of equal forecast accuracy between the factor and alternative models on a pairwise basis. In view of the relatively small number of observations involved, the following small sample version due to Harvey *et al*. (1997) is reported:

$$
\begin{aligned}
DM &= \sqrt{\frac{T+1-2h+h\left(h-1\right)/T}{T}} \cdot \frac{\bar{d}}{\sqrt{V(\bar{d})}} \\
V(\bar{d}) &= \frac{1}{T}\left(\hat{\gamma}_0 + 2\sum_{k+1}^{h-1}\hat{\gamma}_k\right)
\end{aligned}
\tag{8}
$$

where T is the number of forecasts made, h is the forecast horizon, $\bar{d}$ is the mean difference between the squared forecast errors from any two competing models, $V(\bar{d})$ is its approximate asymptotic variance, and $\hat{\gamma}_k$ is the estimated k-th order autocovariance of the forecast error differences. To gauge statistical significance, the modified DM statistics are compared with the one-tailed critical values from the t-distribution with $T-1$ degrees of freedom.

Table 2 **Forecast performances**

Horizon (Quarters)	1	2	3	4
GDP				
Factor	0.33	0.33	0.33	0.53
AR	0.48	0.42	0.42	0.48
VAR	0.77	0.58	0.63	0.78
MFG				
Factor	0.52	0.69	0.91	0.92
AR	0.50	0.65	0.69	0.80
VAR	0.74	1.01	1.09	1.17
SER				
Factor	0.26	0.24	0.45	0.80
AR	0.36	0.48	0.33	0.27
VAR	0.30	0.47	0.55	0.45
CONSTR				
Factor	0.24	0.49	0.46	0.69
AR	0.42	0.54	0.68	0.95
VAR	0.49	0.51	0.64	0.82
CPI				
Factor	0.40	0.58	0.35	1.10
AR	0.42	0.78	1.32	1.80
VAR	0.41	0.84	1.45	2.02

Note: The numbers represent the RMSE statistics for the factor, AR and VAR forecasting models at the various horizons.

A negative Diebold-Mariano statistic in the table indicates that the dynamic factor model shows an improved forecast performance while a positive number implies that the opposite is true. If the difference in accuracy is statistically significant at the 10% level or better, the figure appears in bold. [7] For real GDP and manufacturing growth, the hypothesis of equal predictive accuracy between the dynamic factor and autoregressive models cannot be rejected at conventional significance levels, thus bearing out our earlier assertion that the best-fitting AR(6) models estimated for these two variables represent stiff benchmarks. Still, the factor model is clearly superior to the VAR model here.

[7] In several instances, the Diebold-Mariano statistic cannot be calculated in the usual way because the estimated spectral density at the origin is not guaranteed to be non-negative. When this happens, we use the Bartlett window to estimate the density and set the truncation lag equal to 4, as suggested by Diebold and Mariano (1995).

Table 3 **Tests of predictive accuracy**

Horizon (Quarters)	*GDP*		*MFG*		*SER*		*CONSTR*		*CPI*	
	AR	VAR	AR	VAR	AR	VAR	AR	VAR	AR	VAR
1	–0.80	**–1.58**	0.16	**–1.91**	–1.11	–0.84	**–1.67**	**–2.10**	–0.51	–0.09
2	–0.53	–0.85	0.16	**–1.53**	–1.17	**–1.87**	–0.36	–0.17	–1.23	–1.12
3	–0.80	**–1.86**	0.32	–0.96	0.59	–0.31	**–1.80**	**–1.62**	–1.00	–0.95
4	0.27	–0.26	0.77	–0.75	**1.75**	1.39	**–2.97**	–1.19	–0.90	–0.87

Note: The numbers represent the small sample Diebold-Mariano statistics for the factor model *vis-à-vis* the AR and VAR models. Bold figures denote statistical significance at the 10% level or lower.

In the case of service sector growth, the dynamic factor projections are significantly more accurate than the leading indicator forecasts at $h = 2$, but worse than the univariate predictions at $h = 4$. When it comes to construction growth, however, most of the DM statistics are negative and statistically significant, suggesting that the factor model dominates its two rivals. Unfortunately, the same statistics for price inflation are insignificant, notwithstanding the fact that the prediction errors of the factor model are much smaller those from the AR and VAR models at the longer forecast horizons.

6 Conclusions

Analyzing business cycles in small open economies is no easy task due to the myriad economic shocks that besiege them from time to time. Fortunately, recent developments in factor analysis have provided a parsimonious solution to this problem: first summarize the relevant information in a large macroeconomic dataset—including time series that capture external disturbances—through a small number of dynamic factors. If these account satisfactorily for economic fluctuations, use them to improve on *ex-ante* forecasts of economic aggregates. We show in this paper that such a prescription works well for the small open economy of Singapore.

In our empirical application, an important parameter to determine is the number of ‘optimal’ factors to exploit, which can also be interpreted more informatively as the number of primitive shocks driving business cycles. The results based on a rigorous procedure suggest that four dynamic factors are sufficient to explain over half of the observed macroeconomic fluctuations in Singapore. This is a small number when viewed in an international perspective—typically, five to six factors are needed to explain the same proportion of variance in larger economies. Thus, Singapore's business cycles seem to be caused by a few relatively large shocks originating from the world at large, its neighbours in Asia, the global demand for electronics, and the domestic construction industry.

Regardless of the economic interpretations given to the dynamic factors, prediction based on them can be carried out by using the estimated factors in conjunction with a direct multistep forecasting approach. We find that the recursive forecasts of real activity and price inflation in Singapore produced by the factor model are generally more accurate than those from univariate autoregressions and leading indicator VAR models, even though the differences in forecast performance are not always significant. In conclusion, we might say that the dynamic factor model has proven to be a useful technique for analyzing and forecasting the business cycles of small open economies.

Appendix: Data Listing

Series	Mnemonic	Source	Transformation
Foreign real GDPs (12)			
1. USA	USAGDP	*Econometric Studies Unit, National University of Singapore*	Growth rates
2. Japan	JAPGDP		
3. Korea	KORGDP		
4. Rest of the OECD	ROECDGDP		
5. Malaysia	MALGDP		
6. Indonesia	INDOGDP		
7. Thailand	THAIGDP		
8. Philippines	PHILGDP		
9. Taiwan	TAIGDP		
10. Hong Kong	HKGDP		
11. China	CHINGDP		
12. Foreign GDP	FORGDP		
Foreign leading indexes (6)			
13. USA	USACLI	*SourceOECD*	Deviations from trend
14. Japan	JAPCLI		
15. Germany	GERCLI		
16. UK	UKCLI		
17. 4 big European	EUROCLI		
18. 5 major Asian	ASIACLI		
Foreign stock prices (10)			
19. US	USASPI	*Bloomberg*	Growth rates
20. Japan	JAPSPI		
21. Germany	GERSPI		
22. UK	UKSPI		
23. Korea	KORSPI		
24. Malaysia	MALSPI		
25. Indonesia	INDOSPI		
26. Thailand	THAISPI		
27. Philippines	PHILSPI		
28. Hong Kong	HKSPI		
Foreign real interest rates (3)			
29. US (3-mth LIBOR – CPI Δ)	USAIR	*International Financial Statistics*	Levels
30. Japan (3-mth LIBOR – CPI Δ)	JAPIR		
31. UK (3-mth LIBOR – CPI % Δ)	UKIR		

Series	Mnemonic	Source	Transformation
World electronics (7)			
32. Global semiconductor sales	CHIP	*SIA*	Growth rates
33. US Tech Pulse Index	TECH	*New York Fed*	Growth rates
34. Nasdaq index	NASDAQ	*Bloomberg*	Growth rates
35. US new orders for electronics (excl. semiconductors)	USNO	*US Census Bureau*	Growth rates
36. US shipments-to-inventories ratio for electronics (excl. semiconductors)	USSI	*US Census Bureau*	Growth rates
37. Book-to-bill ratio	BBR	*SEMI*	Levels
38. Electronics Leading Index	ELI	Authors	Growth rates
World prices (3)			
39. Real oil price (Dubai Fateh – World CPI Δ)	OIL	) *International*)	Growth
40. Non-fuel commodity prices	NONOIL	) *Financial*)	rates
41. World CPI	WORLDCPI	) *Statistics*)	
Real GDP components (7)			
42. Real GDP	GDP	))	
43. Private consumption	CON	))	
44. Government consumption	GCON	))	Growth
45. Gross fixed capital formation	GFCF	) *STS*)	rates
46. Transport equipment	GFCFTPT	))	
47. Machinery, equipment & software	GFCFMEQ	))	
48. Net exports	NX	))	
Gross value-added (13)			
49. Manufacturing	MFG	))	
50. Construction	CONSTR	))	
51. Services	SER	))	
52. Commerce	COMM	))	
53. Wholesale & retail trade	WRTRADE	))	
54. Hotels & restaurants*	HOTREST	) *STS*)	Growth
55. Transport & Communications*	TRANSCOM	))	rates
56. Transport & storage*	TRANSTOR	))	
57. Information & communications	INFOCOM	))	
58. Financial & Business Services	FINBIZ	))	
59. Financial services	FIN	))	
60. Business services	BIZ	))	
61. Other Services	OTHER	))	

Series	Mnemonic	Source	Transformation
Industrial production (7)			
62. Total	IIP	STS	Growth rates
63. Electronics	IIPELEC	STS	Growth rates
64. Chemicals	IIPCHEM	STS	Growth rates
65. Biomedicals	IIPBIO	STS	Growth rates
66. Precision engineering	IIPPRE	STS	Growth rates
67. Transport engineering	IIPTPT	STS	Growth rates
68. General manufacturing	IIPGEN	STS	Growth rates
Business surveys (17)			
69. Mfg investment commitments	COMMIT	STS	Growth rates
70. General expectations for mfg	EXPMFG	STS	Net balances of firms
71. Employment expectations for mfg	EMPMFG	STS	Net balances of firms
72. General expectations for services	EXPSER	STS	Net balances of firms
73. Wholesale & retail trade	EXPWRTRADE	STS	Net balances of firms
74. Hotels & catering	EXPHOTREST	STS	Net balances of firms
75. Transport & storage	EXPTRANSTOR	STS	Net balances of firms
76. Financial services	EXPFIN	STS	Net balances of firms
77. Business services	EXPBIZ	STS	Net balances of firms
78. Real estate	EXPESTATE	STS	Net balances of firms
79. Employment expectations for services	EMPSER	STS	Net balances of firms
80. Wholesale & retail trade	EMPWRTRADE	STS	Net balances of firms
81. Hotels & catering	EMPHOTREST	STS	Net balances of firms
82. Transport & storage	EMPTRANSTOR	STS	Net balances of firms
83. Financial services	EMPFIN	STS	Net balances of firms
84. Business services	EMPBIZ	STS	Net balances of firms
85. Real estate	EMPESTATE	STS	Net balances of firms
Construction (14)			
86. GFCF in construction & works	GFCFCONSTR	STS	Growth rates
87. Residential buildings	GFCFRES	STS	Growth rates
88. Non-residential buildings	GFCFNRES	STS	Growth rates
89. Others	GFCFOTHER	STS	Growth rates
90. Contract awards	CA	STS	Growth rates
91. Public	CAPUB	STS	Growth rates
92. Private	CAPTE	STS	Growth rates
93. Residential buildings	CARES	STS	Growth rates
94. Commercial buildings	CACOMM	STS	Growth rates
95. Civil engineering & others	CACIVIL	STS	Growth rates

Series	Mnemonic		Source		Transformation
96. Property price index (residential)	PPIRES	)	*STS*	)	Growth
97. Property price index (office)	PPIOFF	)		)	rates
98. Property price index (shop)	PPISHOP	)		)	
99. Resale price index	RESALE	)		)	
Sectoral Indicators (16)					
100. Retail sales volume	RETAIL	)		)	
101. Car registrations	CAR	)		)	
102. Visitor arrivals*	VISIT	)		)	
103. Air cargo handled	AIR	)		)	
104. Sea cargo handled	SEA	)		)	
105. Electricity generation	ELECTRIC	)		)	
106. Composite leading index	CLI	)		)	
107. Formation of companies	FORM	)	*STS*	)	Growth
108. Manufacturing	FORMMFG	)		)	rates
109. Construction	FORMCONSTR	)		)	
110. Wholesale & retail trade	FORMWRTRADE	)		)	
111. Hotels & restaurants	FORMHOTREST	)		)	
112. Transport & storage	FORMTRANSTOR	)		)	
113. Information & comms	FORMINFOCOM	)		)	
114. Financial & insurance	FORMFIN	)		)	
115. Real estate & leasing	FORMESTATE	)		)	
External Trade (16)					
116. Exports of goods & services	X	)		)	
117. Imports of goods and services	M	)		)	
118. Exports of goods	GX	)		)	
119. Oil	OGX	)		)	
120. Non-oil	NOGX	)		)	
121. Imports of goods	GM	)		)	
122. Oil	OGM	)	*STS*	)	Growth
123. Non-oil	NOGM	)		)	rates
124. Exports of services	SX	)		)	
125. Imports of services	SM	)		)	
126. Domestic exports	DX	)		)	
127. Oil	ODX	)		)	
128. Non-oil	NODX	)		)	
129. Re-exports	RX	)		)	
130. Oil*	ORX	)		)	
131. Non-oil	NORX	)		)	

Series	Mnemonic	Source	Transformation
Price Indices (14)			
132. Export price index	XPI		
133. Oil	OXPI		
134. Non-oil	NOXPI		
135. Import price index	MPI		
136. Oil	OMPI		
137. Non-oil	NOMPI		
138. Terms of trade	TOT	*STS*	Growth
139. Consumer price index	CPI		rates
140. Domestic supply price index	DSPI		
141. Manufactured price index	SMPI		
142. GDP deflator	PGDP		
143. Manufacturing deflator	PMFG		
144. Construction deflator	PCONSTR		
145. Services deflator	PSER		
Labour Market (7)			
146. Changes in employment	EMP		Levels
147. Retrenchments	RETRENCH		Growth rates
148. Unemployment rate (overall)	U	*STS*	Levels
149. Unemployment rate (resident)	URES		Levels
150. Unit labour costs	ULC		Growth rates
151. Manufacturing unit labour costs	MULC		Growth rates
152. Manufacturing unit business costs	MUBC		Growth rates
Financial (17)			
153. Stock prices	SES		Growth rates
154. 3-mth interbank rate	INTER		Levels
155. 1-yr treasury bill yield	TB		Levels
156. 2-yr bond yield	BOND2		Levels
157. 5-yr bond yield	BOND5		Levels
158. Prime lending rate	PLR		Levels
159. Nominal effective exchange rate	NEER	*STS*	
160. Real effective exchange rate	REER		
161. Singapore dollar to US$	USD		
162. Singapore dollar to Pound	POUND		Growth
163. Singapore dollar to Yen	YEN		rates
164. Singapore dollar to Malaysian $	RINGGIT		
165. Singapore dollar to HK$	HKD		

Series	Mnemonic	Source	Transformation
166. Singapore dollar to Korean won	WON		
167. Singapore dollar to Taiwan $	NTD	*STS*	Growth rates
168. Singapore dollar to Indo rupiah*	RUPIAH		
169. Singapore dollar to Thai baht	BAHT		
Monetary (8)			
170. M1	M1		
171. M3	M3		
172. Bank loans	LOAN		
173. Manufacturing	LOANMFG	*STS*	Growth rates
174. Building & construction	LOANCONSTR		
175. Commerce	LOANCOMM		
176. Financial institutions	LOANFIN		
177. Professional & pte individuals	LOANPRO		

Note: Figures in parentheses represent the number of variables in each category. STS refers to the Singapore Department of Statistics online time series database. Time series adjusted for outliers are marked with an asterisk.

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