HONG KONG INSTITUTE FOR MONETARY RESEARCH

A DYNAMIC FACTOR MODEL FOR CURRENT-QUARTER ESTIMATES OF ECONOMIC ACTIVITY IN HONG KONG

Stefan Gerlach and Matthew S. Yiu

HKIMR Working Paper No.16/2004

August 2004

A Dynamic Factor Model for Current-Quarter Estimates of Economic Activity in Hong Kong

Stefan Gerlach
Hong Kong Institute for Monetary Research
University of Basel and CEPR

and

Matthew S. Yiu
Hong Kong Institute for Monetary Research

August 2004

Abstract

This paper applies the single-index dynamic factor model developed by Stock and Watson (1991) to construct current-quarter estimates of economic activity in Hong Kong. The Hang Seng index, a residential property price index, retail sales and total exports are used as coincident indicators. Principal Component Analysis is first used to obtain an impression of the common component of the indicator series. This component and the dynamic factor identified by the Stock-Watson methodology are strongly correlated and seem to account for economic fluctuations in Hong Kong reasonably well.

JEL Classification: E32 E47
Keywords: Business cycles, dynamic factor model, Kalman filtering

---

The views expressed in the paper are solely those of the authors and do not necessarily reflect those of the HKMA, the HKIMR, its Council of Advisers or Board of Directors. We are grateful to the participants of the 8th Australasian Macroeconomics Conference and, in particular, to Yin-wong Cheung, Mark Crosby, Andrew Rose, Nilss Olekalns, Nigel Wilkins, Penelope Smith and Mardi Dungey. Contact information: Stefan Gerlach, HKIMR, 55/F, Two International Finance Centre, 8 Finance Street, Central, Hong Kong, e-mail: stefan_gerlach@hkma.gov.hk; Matthew S. Yiu, HKIMR, 55/F, Two International Finance Centre, 8 Finance Street, Central, Hong Kong, e-mail: matthew_sf_yiu@hkma.gov.hk.

1. Introduction

A clear understanding of the state of macroeconomic activity is important to economic policy making. While GDP data, the broadest measure of economic activity, is only available with a long lag and is subject to several rounds of revisions, many important economic and financial time series that are more readily available can be used to assess the state of activity. In light of this, government agencies, central banks and economic research institutes across the world are routinely producing indicators on the overall macroeconomic condition to be used to assess GDP growth in real time. Much research has been devoted to the issue of how to construct more accurate and timely indicators. In particular, the fact that economic activity evolves in cycles and involves comovements among a large number of economic data has been used to construct reliable estimates of business cycles. This approach has led to an extensive literature developing from the early landmark study by Burns and Mitchell (1946) to the much more formalised approach of Stock and Watson (1989, 1991 and 1993). Burns and Mitchell (1946) develop a list of composite leading, coincident, and lagging indices of business cycles, using a large numbers of economic variables (so-called indicator variables). These indices play an important role in summarising the state of macroeconomic activity in the United States.

Using Burns and Mitchell's notion of business cycles, Stock and Watson (1989, 1991 and 1998) formulate a modern statistical framework to study business fluctuations. They assume that the comovements among variables have a common element that can be captured by a single underlying, unobservable variable and that this unobservable variable represents the general "state of the economy." Next they propose a single-index model that provides a formal definition of the unobservable state of the economy. Using this model, they compute a composite index of coincident indicators.

Since the seminal work of Stock and Watson, the single-index model, also called the dynamic factor model, has been widely used by many other researchers. The recent literature includes Camba-Mendez (2001) and Garcia-Ferrer and Poncela (2002), who modify the model to forecast GDP growth for European countries. For Germany in particular, Bandholz and Funke (2003) use the model to develop leading/coincident indicators of economic activity in the country. In Asia, Fukuda and Onodera (2001) and Chen and Lin (2000) apply the model to improve estimates of the growth of the Japanese economy and to identify turning points and business cycles in Taiwan respectively.

In the case of Hong Kong, preliminary estimates of real GDP figures are published two months after the reference quarter. This arrangement may not be prompt enough to monitor the economy on an ongoing basis. Thus, other indicators of the state of the economy appear warranted.

Partially in light of this, the APEC Study Centre of the Hong Kong University has developed a high frequency macroeconomic forecasting model for Hong Kong.[1] Since the first quarter of 2000, the Centre has been regularly producing quarterly estimates of the growth of Hong Kong GDP using a large number of high frequency financial and macroeconomic variables, Principal Component Analysis (PCA) and the bridge equation approach (Chan 2000).

---

1 High frequency macroeconomic forecasting models for Hong Kong, APEC Study Centre, Hong Kong Institute of Economic and Business Strategy University of Hong Kong. The forecasts are available at http://www.hku.hk/apec/.

In this paper, we use Stock and Watson's dynamic factor model to construct current-quarter estimates and a composite coincident indicator of economic activity in Hong Kong. For computational efficiency, we only use four monthly indicator series–two financial series and two macroeconomic series–for the analysis. Applying the dynamic factor model on the selected indictor series and using the Kalman filter for the estimation of model parameters and state vectors, we generate estimates of the four-quarter growth rate of real GDP in the current quarter. These should be considered as forecasts because the estimates are produced before the real GDP data are known for the quarter in question. To explore how the method works in practice, we use data in the first nine months of 2003 to compute out-sample one-step-ahead forecasts from the dynamic factor model to evaluate its forecasting performance.

This paper proceeds as follows. Section 2 describes the data used in the empirical work of the paper. We select the Hang Seng index, a residential property price index, retail sales and total exports as indicator variables. Section 3 presents the results of applying PCA in order to obtain an impression of the unobservable comovement component. The first Principal Component (PC), which accounts for most variation in the indicator variables, is reasonably correlated with real GDP growth. Section 4 describes the dynamic factor model. The model is transformed into state-space form in order to utilise the Kalman filter for estimation. Section 5 presents the empirical results from using the model and an index of coincident indicators of economic activity in Hong Kong. The dynamic factor seems to account for economic fluctuations in Hong Kong reasonably well. The last section concludes.

2. The Data

Next we explain the choice of indicator series used in the dynamic factor model estimated below. A large number of monthly financial and macroeconomic variables may contain useful information about real economic activity in Hong Kong. Given the range of possible indicator series, we first reduce the dimensionality of the problem by selecting a subset of indicator series: the Hang Seng index, the three-month Hong Kong interbank offer rate, a residential property price index, total exports, retained imports, retail sales, tourist arrivals and electricity consumption.[2] The sample period is from January 1990 to December 2002.

The eight indicator variables are shown in Figure 1. The data are all in logarithms, except the HIBOR series which is in percentage points. Furthermore, we have seasonally adjusted the five macroeconomic variables using the X-12 method. The figure suggests that all variables can be characterised as having a stochastic trend, except the interest rate series.

To improve computational efficiency, it would be desirable to use a subset of these eight series. In order to select the series that are more informative for real activity, we first look at the contemporaneous correlation among their twelve-month growth rates and the four-quarter rate of the real GDP growth of Hong Kong.[3] Since GDP data are quarterly, the growth rate of GDP needs to be converted into monthly

[2] The data and the Hong Kong real GDP growth come from the CEIC Data Ltd database.

[3] We have not calculated the cross-correlation function for real GDP and each indicator series since the objective of this study is to produce current quarter estimates.

frequency in order to calculate the correlations. For simplicity, we assume that the three monthly growth rates in each quarter are equal to the quarterly growth rate of real GDP.

Table 1 shows the correlation matrix of the twelve-month growth rates of each of the eight series (for interest rates we use the level of the series) and four-quarter real GDP growth.

It is clear that all indicator series, except electricity consumption, display considerable correlation with real GDP growth. While the HIBOR series shows negative correlation with real GDP as expected, the Hang Seng Index, the property price index, total exports, retail sales and retained imports are strongly positively correlated with GDP. Preliminary estimates of the model showed that, if both total exports and retained imports are in the model, one of them is insignificant. This may be due to the fact that they are highly mutually correlated. Thus, we select the Hang Seng Index, the property price index, retail sales and total exports as coincident indicators for the empirical work.

These selected four indicator series all have a unit root, confirmed by augmented Dickey-Fuller tests at the 5% significance level. Furthermore, under the assumption of no deterministic trends in the series with a restricted intercept in the cointegration relation, a Johansen test indicates no cointegration at the 5% significant level. On the other hand, if they are cointegrated, different modelling strategies are needed for unobservable-component models.[4]

3. Principal Components Analysis

To obtain an impression of the unobservable comovement component of the four indicator series, we first apply PCA to extract the major underlying components from the data. It is well known that the general objectives of PCA, which explains the variance-covariance structure of the data using linear combinations of the original variables, are data reduction and interpretation.[5]

Figure 2 shows the twelve-month growth rates of the four indicator series. We find that if we apply PCA to data, the first PC is strongly correlated with real GDP growth. The correlation between the first PC and four-quarter real GDP growth is 0.83, much larger than that, 0.09, of the second PC (see Table 2). The third and fourth PCs are weakly correlated with the real GDP growth with correlation coefficients of 0.16 and -0.18 respectively.

Table 2 shows that the first PC accounts for 69 percentage of the total variation among the four indicators. This can be interpreted that the four indicators have a strong underlying component among them. Table 2 also shows the loading of the each of the four PCs. The four indicators have similar loading on to the first PC, whereas their loading on to the other three PCs are very divergent.

4 Harvey, Fernandez-Macho, and Stock (1987) discuss modelling strategies for unobservable-component models with cointegrated variables.

5 For a good introduction to the theory and the applications of PCA, see Jolliffe (1986).

In light of the high correlation between the first PC and four-quarter real GDP growth, it appears that there is an unobservable common component among the twelve-month growth rates of the four indicator series that is likely to give a good indication of overall real economic activity in Hong Kong. We, therefore, explore this further using the dynamic factor model proposed by Stock and Watson.[6]

4. The Dynamic Factor Model

In this section we present the dynamic factor model we use to extract the unobservable common component and to develop a composite coincident index for the Hong Kong economy. We first outline the model, show how it can be written in state-space form and discuss how to estimate it using Kalman filtering and maximum likelihood.

4.1 Specification

The dynamic factor model can be formulated in terms of the twelve-month growth rates of the four indicator variables as follows:[7]

(1) $$\Delta Y_{it} = D_i + \gamma_i \Delta C_t + u_{it}, \qquad i = 1,...,4$$

(2) $$(\Delta C_t - \delta) = \phi_1(\Delta C_{t-1} - \delta) + ... + \phi_p(\Delta C_{t-p} - \delta) + \eta_t, \qquad \eta_t \sim i.i.d.N(0, \sigma_\eta^2)$$

(3) $$u_{it} = d_{i1}u_{it-1} + ... + d_{iq}u_{it-q} + \nu_{it}, \qquad \nu_{it} \sim i.i.d.N(0, \sigma_\nu^2) \text{ and } i = 1,...,4$$

where Y_{it} denotes the logarithm of series i and ΔY_{it} denotes $Y_{it} - Y_{it-12}$.

In the above model, Y_{it} consists of two stochastic components: an unobservable common component ΔC_t and an idiosyncratic component u_{it}. Both of these components are modelled as autoregressive stochastic processes, $\mathrm{AR}(p)$ and $\mathrm{AR}(q)$, respectively. For a normalisation, the scale of ΔC_t is identified by setting σ_η^2 to unity. In addition, all shocks are assumed to be independent.

The main identifying assumption in the above model is that the comovements of the indicator series arise from the single source C_t. In other words, ΔC_t enters each with a different weights, γ_i, $i = 1,...,4$. We further assume that u_{it} and ΔC_t are mutually uncorrelated at all leads and lags for all series.

Note that, as the parameters D_i and δ are not separately identified, Stock and Watson (1991) suggest writing the model in deviation from means, thus concentrating the D_i and $\gamma_i\delta$ terms out of the likelihood function:

6 A number of problems in empirical business cycle analysis are naturally studied using Kalman filtering. For instance, Gerlach and Yiu (2004) use Kalman filtering to estimate output gaps in eight Asian economies.

7 This means that adjustments for seasonal factors are not needed.

(4) $$\Delta y_{it} = \gamma_i \Delta c_t + u_{it}, \qquad i = 1,...,4$$

(5) $$\Delta c_t = \phi_1 \Delta c_{t-1} + ... + \phi_p \Delta c_{t-p} + \eta_t, \qquad \eta_t \sim i.i.d. N(0,1)$$

(6) $$u_{it} = d_{i1} u_{it-1} + ... + d_{iq} u_{it-q} + \nu_{it}, \qquad \nu_{it} \sim i.i.d. N(0, \sigma_i^2) \text{ and } i = 1,...,4$$

where and $\Delta y_{it} = \Delta Y_{it} - \Delta \overline{Y}_i$ and $\Delta c_t = \Delta C_t - \delta$.

As the dynamic factor model in deviation from means is linear in the unobservable components, we can use the Kalman filter to construct the Gaussian likelihood function and to estimate the unknown parameters by maximum likelihood . However, to use the Kalman filter, we have to transform the above three equations into state space form.[8]

4.2 State-Space Representation

The state space form of the system is comprised of a measurement equation and a transition (or state) equation. The measurement equation, which relates the observed variables to the elements of the state vector, is given by (assuming p=2 for Δc_t q=1 for u_{2t}, u_{3t}, u_{4t} except u_{1t} which follows a AR(2) process):

(7) $$\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \\ \Delta y_{4t} \end{bmatrix} = \begin{bmatrix} \gamma_1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \gamma_3 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \gamma_4 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \\ u_{1t} \\ u_{1t-1} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ C_{t-1} \end{bmatrix}$$

The transition equation, which describes the evolution of the unobservable state vector, which in our case contains Δc_t and u_{it} and their lags can be written:

(8) $$\begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \\ u_{1t} \\ u_{1t-1} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ C_{t-1} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & d_{11} & d_{12} & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & d_{21} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & d_{31} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & d_{41} & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} \Delta c_{t-1} \\ \Delta c_{t-2} \\ u_{1t-1} \\ u_{1t-2} \\ u_{2t-1} \\ u_{3t-1} \\ u_{4t-1} \\ C_{t-2} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ \nu_{1t} \\ 0 \\ \nu_{2t} \\ \nu_{3t} \\ \nu_{4t} \\ 0 \end{bmatrix}$$

[8] For a discussion of state-space models and the Kalman filter, see Harvey (1989, 1990) or Hamilton (1994).

where $\begin{bmatrix}\eta_t & 0 & \nu_{1t} & 0 & \nu_{2t} & \nu_{3t} & \nu_{4t} & 0\end{bmatrix}$ is the vector of disturbances, which we assume has a diagonal covariance matrix. This assumption implies that shocks to the unobservable common component and the idiosyncratic components are mutually uncorrelated at all leads and lags.

4.3 Estimation

As mentioned before, to estimate the model we form the likelihood function:

(9) $$\log\ L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{1}^{T}\log|F_t| - \frac{1}{2}\sum_{1}^{T} v_t^T F_t^{-1} v_t\ ,$$

where T, v_t and F_t denote the sample size, the prediction errors and the mean square matrix of the prediction errors, respectively. Estimates of the model can then be obtained by numerically maximising the likelihood function, using the Kalman filter. Since the indicator variables are non-stationary, in estimating the model we follow the suggestions of Harvey (1989) and assume that the prior state vector is a random variable and has a diffuse distribution, that is, we assume that its covariance matrix is given by κI with $\kappa \to \infty$. This is tantamount to assuming that nothing is known about the initial state.

5. Empirical Results

Table 3 presents the estimates of ϕ , γ and the variances of the disturbances in two dynamic factor models on the four indicator series (in the order of the Hang Seng index, the property price index, retail sales and total exports), with the estimation period from January 1991 to December 2003. The first model has a AR(2) process for the unobservable common component, whereas a AR(3) process is specified for the same component in the second model. The idiosyncratic components are all assumed to follow a AR(1) process, except the Hang Seng index which follows a AR(2) process.

All parameters are significant at the 5% level in the first model. However, for the second model, the third parameter of the AR(3) process is not significant at the 5% level. The two model selection criteria, the Akaike information criterion and the Hannan-Quinn criterion, also show that the first model is better than the second model.

With regard to the estimated autoregressive coefficients in the first model, the roots of $\phi(B)$ all lie outside the unit circle and are a pair of complex conjugates. Thus, the estimated AR(2) process for Δc_t is stationary and exhibits a cyclical pattern. Regarding the idiosyncratic components, since in the model fitting process, the estimated parameter for u_{3t} is not significant at the 5% level, we, thus, cannot reject the hypothesis that u_{3t} equals zero. Therefore, the twelve-month growth rate of the retail sales series is just an AR(2) process plus white noise.

In order to check the adequacy of the model specification, we analyse the standardised disturbances ν_i. If the model is well specified and the parameters are known, the residuals $\hat{\nu}_i$ should be randomly distributed. In practice, however, the parameters are estimated and the residuals are therefore only approximately random (see Harvey 1989, p.256). This can be checked in a number of ways, for instance by performing Ljung-Box tests on the autocorrelations of $\hat{\nu}_i$. The results are satisfactory except for $\hat{\nu}_4$.

Furthermore, we use Jarque-Bera tests to test the normality of the residuals.[9] The tests, however, show mixed results. Without normality, the Kalman filter will not be the best linear estimator in the sense of achieving a minimum variance for estimation. Despite these minor problems, the overall impression is that the first model fits the data well. Given the estimated parameters, we obtain the unobservable common component by running the Kalman smoother.

Figures 3 plots the standardised, estimated unobservable common component, Δc_t, against the standardised twelve-month growth rates of each of the four indicator series.[10] The unobservable common component evolves over time in a way similar to the first three indicator series, in particular the retail sales series. Regarding the factor loading of the four indicator series, the total exports series has a somewhat smaller weight. The PCA above also yielded similar results. We also find that, if we discard any one of the four series, the estimated Δc_t will be correlated much less with the four-quarter GDP growth.

Using the same variance as the GDP growth, we adjust ΔC_t and plot it against the four-quarter GDP growth in Figure 4, with the two standard error confidence bands. The contemporaneous correlation between the two series is very high, 0.86, which is even higher than that between the first PC and GDP growth. Although the model tracks GDP growth reasonably well in the whole estimation period, it somewhat under-estimates GDP growth in 2000 and over-estimates growth in 2001. It is possible that some structural changes in those years have made the four indicator series less informative.

In order to explore the usefulness of the model, we use the model to generate one-step-ahead forecasts of the unobserved factor for the first nine months in 2003. The one-step-ahead forecast is generated with the estimation period up to the previous month, e.g. we use data from January 1991 to February 2003 to generate the one-step-ahead forecast for March 2003. Figure 5 plots the nine one-step-ahead forecasts against the four-quarter GDP growth of the first three quarters of 2003, with the two standard error confidence bands. Thus, they appear to do a reasonably good job in predicting out sample.

The dynamic factor model also enables us to construct an index of coincident indicators of economic activity in Hong Kong. However, as the model is estimated in the form of deviation from means, we need to estimate the mean growth rate for the common component ΔC_t. This mean is calculated as a weighted average of the growth rates of the indicator series. The weights are those implicitly used to construct ΔC_t from the indicator variables and can be estimated from the Kalman Filter algorithm.[11] The estimated, adjusted mean growth rate for ΔC_t is 3.37 percentage points. Figure 6 shows the index of coincident indicators of economic activity in Hong Kong, constructed by applying the above dynamic factor model on the four indicator series. The series is listed in Table 4.

[9] For the details, see Jarque and Bera (1980).

[10] That is, we have adjusted the series so that they have zero mean and unit variance.

[11] For the details of the calculation, see Stock and Watson (1989).

6. Conclusion

We have shown that both the dynamic factor model and PCA are useful in assessing current-quarter real economic activity in Hong Kong. As the Hong Kong GDP figures are published with a time lag of two months, our approach can produce estimates of the GDP growth of the same quarter, particularly on showing any turning points before the dissemination. The advantage of the dynamic factor model over PCA is that it can also generate multi-steps-ahead forecasts with confidence bands that may be of use for economic policy making.

We have also constructed an index of coincident indicators of economic activity in Hong Kong from the dynamic factor model. With the availability of this index, we can adopt the methodology of state-space models with regime switching, developed by Kim (1994), to identify the business cycle fluctuations in Hong Kong in future work.[12]

[12] For the details of the methodology, see Kim and Nelson (1999).

References

Bandholz, H. and M. Funke (2003), "In Search of Leading Indicators of Economic Activity in Germany," forthcoming in Journal of Forecasting.

Burns, A. F., and W. A. Mitchell (1946), *Measuring Business Cycles*, New York: NBER.

Camba-Mendez, G., R. J. Smith, G. Kapetanios, and M. R. Weale (2001), "An Automatic Leading Indicator of Economic Activity: Forecasting GDP Growth for European Countries," *Econometrics Journal*, 4: 556-90.

Chan, C. S. (2000), "High Frequency Macroeconomic Forecasting Model for Hong Kong," APEC Study Centre, Hong Kong Institute of Economic and Business Strategy, University of Hong Kong.

Chen, S. and J. Lin (2000), "Identifying Turning Points and Business Cycles in Taiwan: A Multivariate Dynamic Markov-Switching Factor Model Approach," *Academic Economic Papers*, 28: 289-320.

Diebold, F. X., and G. D. Rudebusch (1996), "Measuring Business Cycles: A Modern Perspective," *The Review of Economics and Statistics*, 78: 67-77.

Fukuda, S. and T. Onodera (2001), "A New Composite Index of Coincident Economic Indicators in Japan: How Can We Improve Forecast Performances?" *International Journal of Forecasting*, 17: 483-98.

Garcia-Ferrer, A. and P. Poncela (2002), "Forecasting European GNP Data through Common Factor Models and other Procedures," *Journal of Forecasting*, 24: 225-44.

Gerlach, S. and M. S. Yiu (2004), "Estimating Output Gaps in Asia: A Cross-Country Study," *Journal of the Japanese and International Economies*, 18: 115-36.

Hamilton, J. D. (1994), *Time Series Analysis*, Princeton NJ: Princeton University Press.

Harvey, A. C. (1989), *Forecasting, Structure Time Series Models and the Kalman Filter*, Cambridge: Cambridge University Press.

Harvey, A. C. (1990), *The Econometric Analysis of Time Series*, 2nd ed., Cambridge: MIT Press.

Harvey, A.C, F.J. Fernandez-Macho, and J.H.Stock (1987), "Forecasting and Interpolation Using Vector Autoregressions with Common Trends," *Annales d'Economie et de Statistique*, No.6-7: 279-88.

Jarque, C. M. and A. K. Bera (1980), "Efficient Tests for Normality, Heteroskedasticity, and Serial Independence of Regression Residuals," Economics Letters, 5: 255-59.

Jolliffe, I. T. (1986), *Principal Component Analysis*, New York: Springer Verlag.

Kim, C., (1994), “Dynamic Linear Models with Markov-Switching,” *Journal of Econometrics*, 60: 1-22.

Kim, C., and C. R. Nelson (1999), *State-Space Models with Regime Switching*, Cambridge, Massachusetts: The MIT Press.

Stock, J. H., and M. W. Watson (1989), “New Indexes of Coincident and Leading Economic Indicators”, in O. Blanchard, and Fischer, S., eds., *NBER Macroeconomic Annual 1989*, Cambridge MA: MIT Press: 351-94.

Stock J. H., and M. W. Watson (1991), “A Probability Model of the Coincident Economic Indicators,” in Lahiri, K., and Moore, G., eds., *Leading Economic Indicators New Approaches and Forecasting Records*, New York: Cambridge University Press: 63-85.

Stock J. H., and M. W. Watson (1993), “A Procedure for Predicting Recession with Leading Indicators: Econometric Issues and Recent Experience,” in J.H. Stock, and M.W. Watson, eds., *Business Cycles, Indicators and Forecasting*, University of Chicago Press for NBER: 255-84.

Stock, J. H., and M. W. Watson (1998), “Business Cycle Fluctuations in U.S. Macroeconomic Times Series,” NBER Working Paper No. 6528, Cambridge MA: National Bureau of Economic Research.

Table 1. Correlation Matrix of the Eight Indicators and Real GDP Growth

	Hang Seng Index	3-month Interbank Rate	Property Price Index	Total Exports	Retained Imports	Retail Sales	Tourist Arrivals	Electricity Consumption	Real GDP
Hang Seng Index	1.00								
3-month Interbank Rate	-0.15	1.00							
Property Price Index	0.60	-0.12	1.00						
Total Exports	0.49	-0.04	0.51	1.00					
Retained Imports	0.41	0.09	0.41	0.75	1.00				
Retail Sales	0.67	-0.33	0.69	0.52	0.39	1.00			
Tourist Arrivals	0.18	-0.51	-0.09	0.23	0.08	0.31	1.00		
Electricity Consumption	-0.20	0.10	0.03	0.19	0.13	0.02	0.08	1.00	
Real GDP	0.72	-0.15	0.58	0.69	0.66	0.78	0.29	-0.01	1.00

Table 2. Principal Component Analysis

	First Principal Component	Second Principal Component	Third Principal Component	Fourth Principal Component
Eigenvalue	2.75	0.56	0.40	0.30
Variance Proportion	0.69	0.14	0.10	0.07
Cumulative Proportion	0.69	0.83	0.93	1.00
Eigenvector				
Hang Seng Index	0.51	-0.31	0.74	0.33
Property Price Index	0.51	-0.21	-0.67	0.50
Retail Sales	0.53	-0.25	-0.11	-0.80
Total Exports	0.45	0.89	0.07	0.01
Correlation with GDP	0.83	0.09	0.16	-0.18

Table 3. Maximum Likelihood Estimates

Estimation period: January 1991 to December 2002

Model	AR(2) for the unobservable common component		AR(3) for the unobservable common component	
Parameters	Estimates	Asymptotic t-values	Estimates	Asymptotic t-values
ϕ_1	1.815	115.068	1.812	18.075
ϕ_2	-0.833	-48.816	-0.868	-6.187
ϕ_3	—	—	0.328	0.656 *
$d_{1,1}$	1.196	19.184	1.168	13.324
$d_{1,2}$	-0.348	-5.340	-0.273	-3.057
$d_{2,1}$	0.982	38.050	0.983	35.669
$d_{4,1}$	0.373	4.774	0.375	5.016
γ_1	0.048	4.504	0.084	4.157
γ_2	0.053	6.395	0.071	6.074
γ_3	0.058	6.723	0.078	7.448
γ_4	0.043	4.384	0.057	4.443
σ_{u1}^2	0.086	9.541	0.095	8.255
σ_{u2}^2	0.020	8.416	0.022	7.844
σ_{u3}^2	0.214	9.559	0.194	10.237
σ_{u4}^2	0.499	8.559	0.494	8.869
Log Likelihood	-283.251		-280.703	
Akaike info. Criterion	4.127		4.107	
Hannan-Quinn criterion	4.244		4.232	
Diagnostics:	Test Stat.	Prob-Values	Test Stat.	Prob-Values
LB(ν_1)	5.094	0.532	8.386	0.211
LB(ν_2)	10.104	0.101	14.828	0.025
LB(ν_3)	4.598	0.596	5.111	0.530
LB(ν_4)	29.112	0.000	29.877	0.000
JB(ν_1)	0.052	0.974	0.378	0.828
JB(ν_2)	8.844	0.015	10.993	0.004
JB(ν_3)	177.100	0.000	163.122	0.000
JB(ν_4)	42.375	0.000	44.658	0.000

Note: LB(ν_1): Ljung-Box Q test for AR(6) residual autocorrelation; JB(ν_1): Jarque-Bera test for normality of the residual series.

* Not significant at the 5% level.

Table 4. Composite Coincident Indicator

January 1991	100.00	August 1994	125.04
February 1991	100.83	September 1994	125.40
March 1991	101.64	October 1994	125.54
April 1991	103.11	November 1994	125.57
May 1991	104.41	December 1994	125.48
June 1991	105.70	January 1995	124.65
July 1991	106.85	February 1995	125.07
August 1991	107.79	March 1995	125.33
September 1991	108.54	April 1995	125.93
October 1991	109.20	May 1995	126.23
November 1991	109.66	June 1995	126.40
December 1991	110.04	July 1995	126.28
January 1992	109.48	August 1995	126.46
February 1992	110.16	September 1995	126.72
March 1992	110.81	October 1995	126.91
April 1992	112.05	November 1995	127.19
May 1992	113.20	December 1995	127.53
June 1992	114.22	January 1996	127.07
July 1992	114.73	February 1996	127.78
August 1992	115.28	March 1996	128.16
September 1992	115.69	April 1996	128.79
October 1992	115.84	May 1996	129.14
November 1992	116.05	June 1996	129.38
December 1992	116.28	July 1996	129.33
January 1993	115.72	August 1996	129.64
February 1993	116.41	September 1996	130.05
March 1993	117.05	October 1996	130.40
April 1993	118.19	November 1996	130.79
May 1993	119.10	December 1996	131.23
June 1993	119.82	January 1997	130.86
July 1993	120.10	February 1997	131.65
August 1993	120.53	March 1997	132.16
September 1993	120.98	April 1997	132.93
October 1993	121.33	May 1997	133.59
November 1993	121.85	June 1997	133.87
December 1993	122.51	July 1997	133.61
January 1994	122.37	August 1997	133.53
February 1994	123.22	September 1997	133.21
March 1994	123.75	October 1997	132.46
April 1994	124.39	November 1997	131.34
May 1994	124.64	December 1997	130.26
June 1994	124.80	January 1998	128.35
July 1994	124.69	February 1998	127.92

Table 4. Composite Coincident Indicator (continue)

March 1998	127.62	August 2000	134.40
April 1998	127.64	September 2000	134.87
May 1998	127.17	October 2000	135.06
June 1998	126.40	November 2000	135.19
July 1998	125.52	December 2000	135.39
August 1998	125.05	January 2001	134.83
September 1998	124.85	February 2001	135.44
October 1998	124.82	March 2001	135.84
November 1998	125.07	April 2001	136.55
December 1998	125.36	May 2001	136.87
January 1999	124.71	June 2001	136.96
February 1999	125.21	July 2001	136.62
March 1999	125.74	August 2001	136.49
April 1999	126.80	September 2001	136.40
May 1999	127.59	October 2001	136.24
June 1999	128.22	November 2001	136.30
July 1999	128.51	December 2001	136.52
August 1999	129.04	January 2002	135.95
September 1999	129.60	February 2002	136.53
October 1999	130.10	March 2002	136.87
November 1999	130.75	April 2002	137.49
December 1999	131.53	May 2001	137.79
January 2000	131.40	June 2002	137.87
February 2000	132.25	July 2002	137.61
March 2000	132.73	August 2002	137.63
April 2000	133.41	September 2002	137.72
May 2000	133.67	October 2002	137.74
June 2000	133.87	November 2002	137.90
July 2000	133.95	December 2002	138.16

Figure 1. Indicator Series (in logarithms, except interest rate)

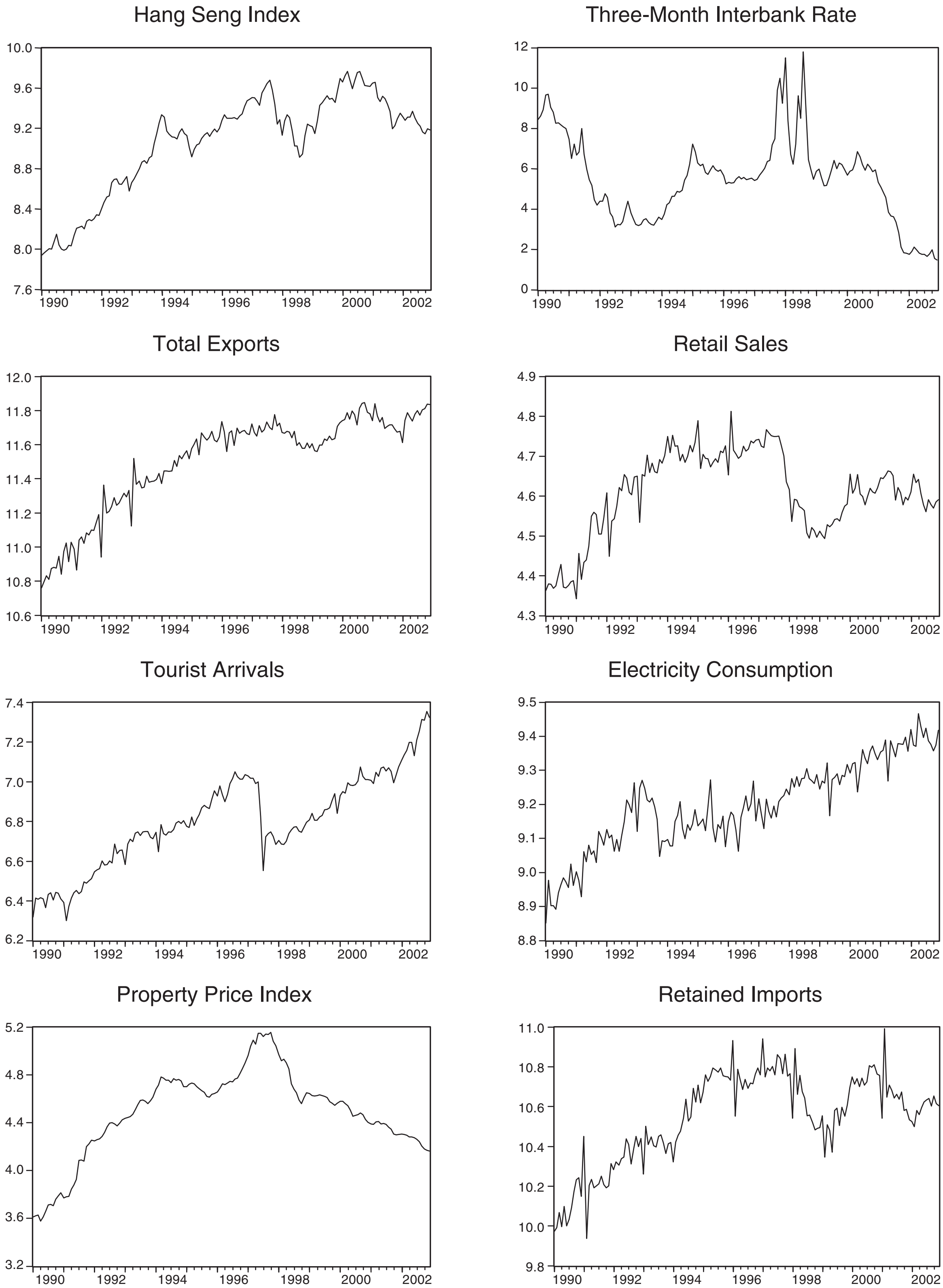

Figure 2. Selected Indicators (Standardised 12-month Growth Rate)

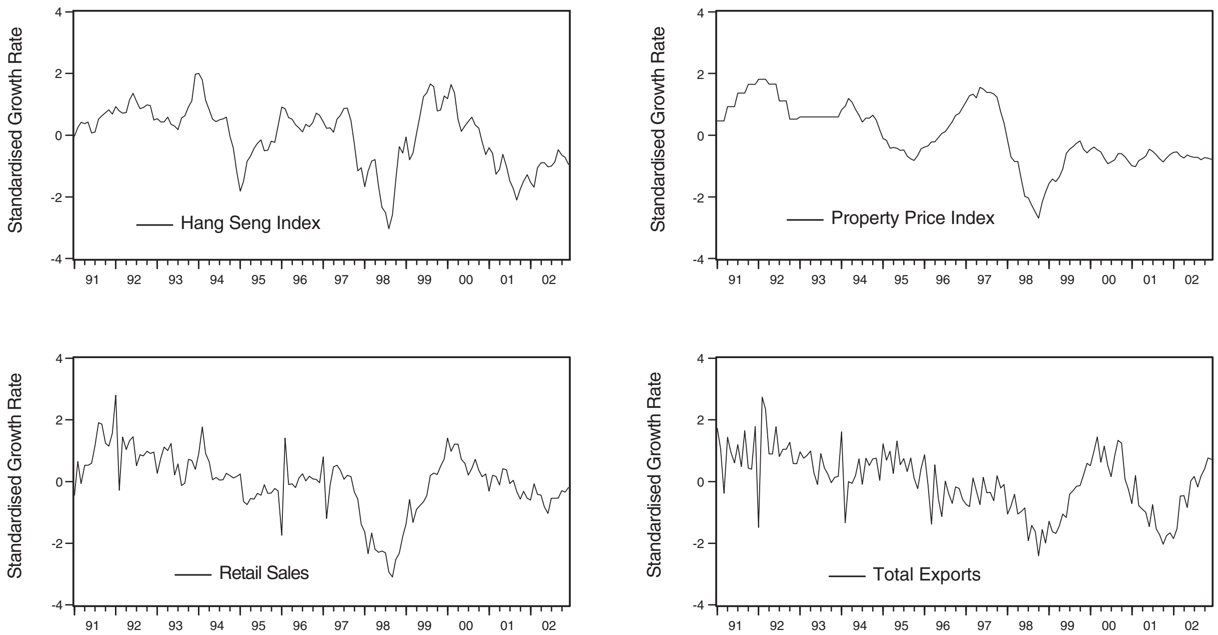

Figure 3. Indicator Series and Commont Component

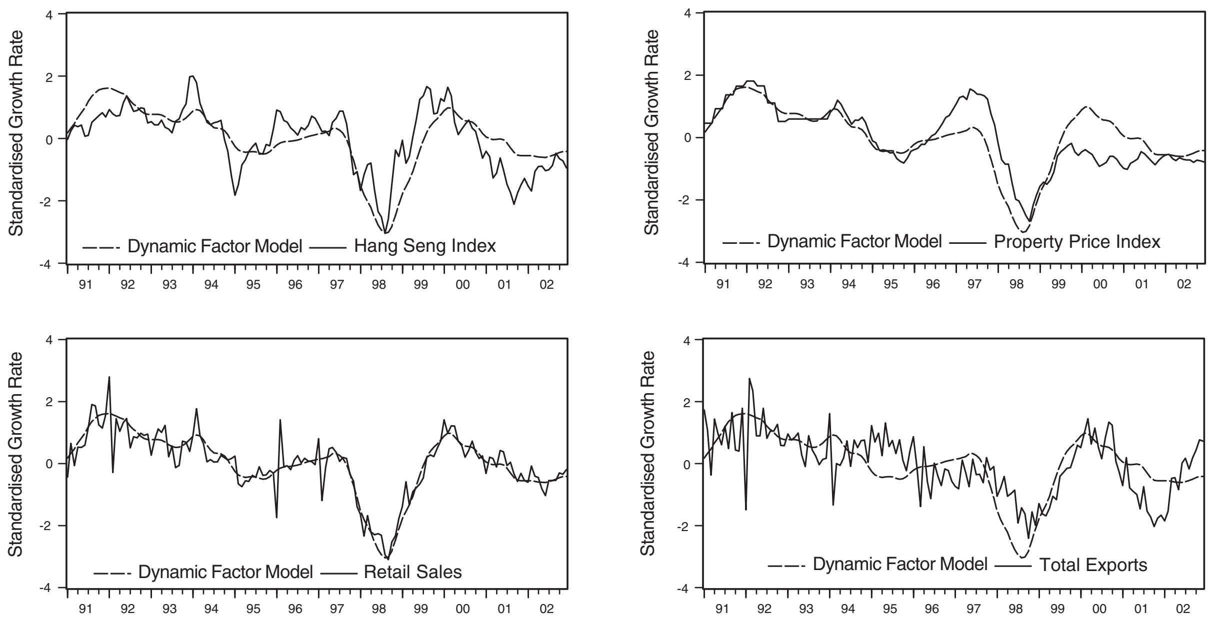

Figure 4. Common Component and Real GDP (together with 95% confidence bands)

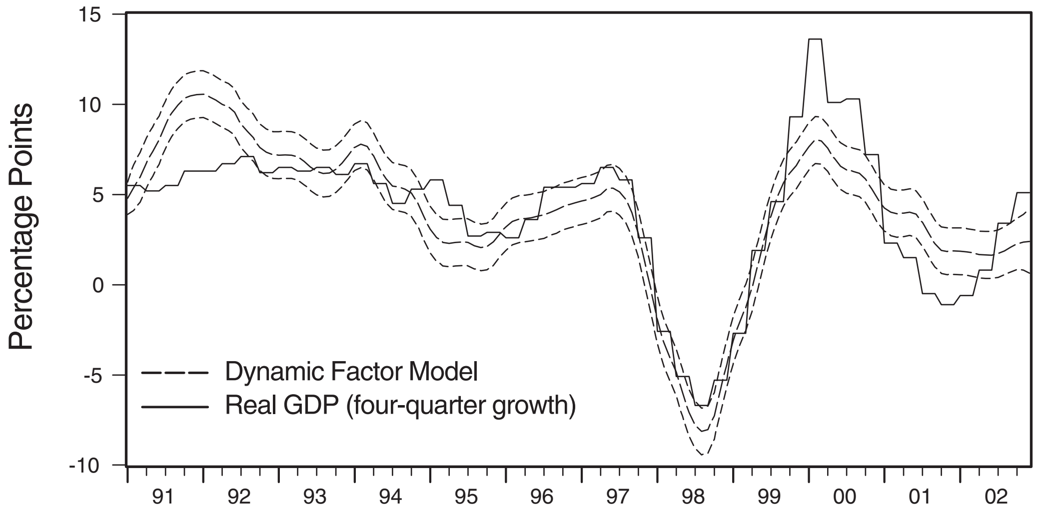

Figure 5. Out of Sample Forecasts (from January to September 2003)

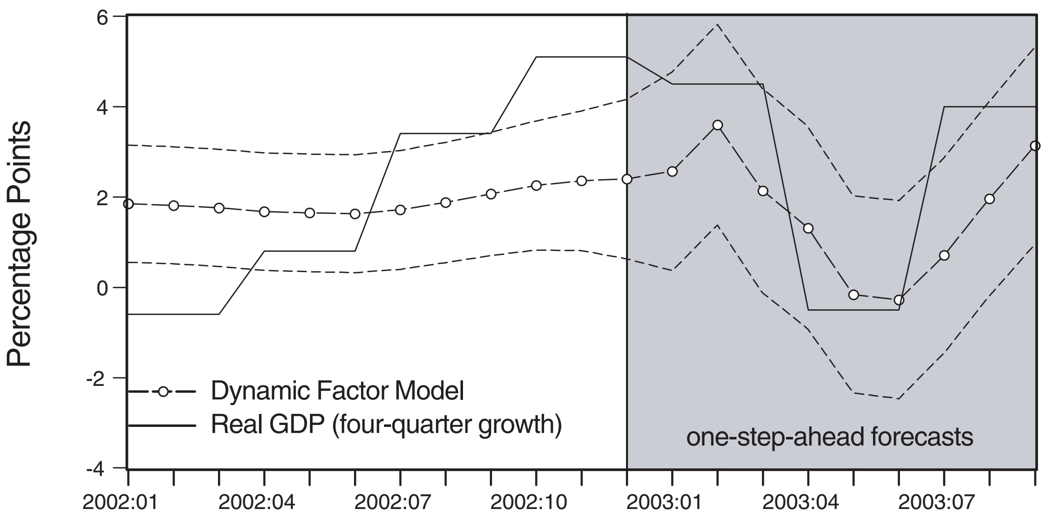

Figure 6. Composite Conincident Indicator of Hong Kong