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A DYNAMIC FACTOR MODEL OF ECONOMIC ACTIVITY IN HONG KONG

Stefan Gerlach* *Bank for International Settlements; University of Basel; CEPR*
Matthew S. Yiu *Hong Kong Institute for Monetary Research*

Abstract. This paper applies the single-index dynamic factor model developed by J. H. Stock and M. W. Watson to construct (almost) real-time 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 capture economic fluctuations in Hong Kong reasonably well.

1. INTRODUCTION

A clear understanding of the state of macroeconomic activity is important for economic policy-making. While GDP data, the broadest measure of economic activity, are available only with a long lag and are subject to several rounds of revisions, many important economic and financial time series that are more rapidly 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 of macroeconomic conditions that can be used to assess GDP growth in real time.

Much of this work follows the seminal study by Burns and Mitchell (1946), who develop a list of composite leading, coincident and lagging indices of business cycles, using a large number of economic variables (so-called indicator variables). Formalizing this approach, and relying on the fact that economic cycles are associated with co-movements of many macroeconomic time series, Stock and Watson (1989, 1991 and 1998) propose a modern statistical framework to study fluctuations in economic activity. They assume that the co-movements among variables have a common element that represents the general 'state of the economy'. Next, they propose a single-index model that provides a formal definition of this unobservable state of the economy, and compute a composite index of coincident indicators to capture it.

**Address for correspondence:* Stefan Gerlach, Bank for International Settlements, CH-4002 Basel, Switzerland; Email: stefan.gerlach@bis.org; matthew_sf_yiu@hkma.gov.hk. The views expressed in the paper are solely our own and do not necessarily reflect those of the BIS, the HKIMR, its Council of Advisers or Board of Directors. We are grateful to an anonymous referee; to the participants of the 8th Australasian Macroeconomics Workshop, and in particular to Yin-wong Cheung, Mark Crosby, Andrew Rose, Nilss Olekalns, Nigel Wilkins, Penelope Smith and Mardi Dungey, for comments.

Since the seminal work of Stock and Watson, the single-index model, also called the dynamic factor model, has been widely used. The recent literature includes Camba-Mendez *et al.* (2001) and Garcia-Ferrer and Poncela (2002), who modify the model to forecast GDP growth for several European economies, and Bandholz and Funke (2003), who use the model to develop leading and coincident indicators of economic activity in Germany. Fukuda and Onodera (2001) and Chen and Lin (2000) apply the model to Japan and to Taiwan, respectively.

In Hong Kong, preliminary estimates of real GDP are published two months after the reference quarter and are subsequently revised. These arrangements, which are similar to those of many other economies, make it difficult to use GDP data to monitor the economy in (almost) real time. Thus, other indicators of the state of the economy are warranted.[1] In this paper we use Stock and Watson's dynamic factor model to construct a composite coincident indicator of economic activity in Hong Kong in the period from January 1991 to December 2002. For computational efficiency, we only use four monthly indicator series – two financial series and two macroeconomic series – in the analysis. Applying the dynamic factor model to the selected indicator series, and using the Kalman filter to estimate the model parameters and the state vectors, we generate estimates of the underlying state of real economic conditions in the current month. To explore how well the method works in practice, we use data from the first nine months of 2003 to compute out-of-sample one-step-ahead predictions from the dynamic factor model to evaluate its predictive performance.

The paper proceeds as follows. Section 2 describes the data used in the empirical work. We selected the Hang Seng index, a residential property price index, retail sales and total exports as indicator variables. Section 3 explains how we applied principal component analysis (PCA) to obtain an impression of the unobservable common component. Section 4 describes the dynamic factor model. The model is transformed into state–space form in order to utilize the Kalman filter for estimation. Section 5 presents the empirical results and the estimated index of coincident indicators of economic activity in Hong Kong. The dynamic factor seems to capture economic fluctuations in Hong Kong reasonably well. The final section concludes.

2. THE DATA

In this section 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

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

reduced the dimensionality of the problem by investigating eight indicator series.[2]

However, for computational reasons, it was desirable to use a subset of these eight series. In order to select the subset that is most informative about real activity, we first looked at the contemporaneous correlations of their 12-month growth rates and the four-quarter rate of real GDP growth of Hong Kong. Since the GDP data are quarterly, the growth rate of GDP needs to be converted into monthly frequency in order to calculate the correlations. For simplicity, we assumed 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 12-month growth rates of each of the eight series and the four-quarter real GDP growth for the sample period January 1991–December 2002. Because of their strong correlations with real GDP growth, the Hang Seng index, the residential property price index, total exports and retail sales were selected for the proposed dynamic factor model.

Although retained imports are also quite strongly positively correlated with GDP, preliminary estimates of the dynamic factor model showed that, if both total exports and retained imports were included in the model, one of them would be insignificant. (This may be due to the fact that they are highly correlated.) For this reason, we decided not to use retained imports in the empirical work below.

The four indicator series selected all have a unit root, as evidenced by augmented Dickey–Fuller tests.[3] Furthermore, a Johansen test indicates no cointegration at the 5% significance level.[4] This finding is important, since, if the series are cointegrated, different modelling strategies are needed for the unobservable-component model.[5]

3. PRINCIPAL COMPONENTS ANALYSIS

Figure 1 shows the 12-month growth rates of the four indicator series and the four-quarter growth rate of real GDP in Hong Kong. To obtain an impression of the co-movements of the four indicator series, we first applied PCA to extract the underlying common components from the data.[6] We found that 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

[2] The eight series were 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. The series and the Hong Kong real GDP data come from CEIC Data Ltd.

[3] The series are seasonally adjusted before the unit root test. The tests assume both a constant and a trend, with a maximum lag of 13. For a discussion of the lag order and critical values for an Augmented Dickey–Fuller test, see Cheung and Lai (1995).

[4] The test assumes no deterministic trends in the series, but allows for a restricted intercept in any cointegrating relation.

[5] Harvey *et al.* (1987) discuss modelling strategies for unobservable-component models with cointegrated variables.

[6] For a good introduction to the theory and the applications of PCA, see Jolliffe, (2002).

Table 1. Correlation matrix of the eight indicators and real GDP growth, sample period January 1991– December 2002

	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							
Residential 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

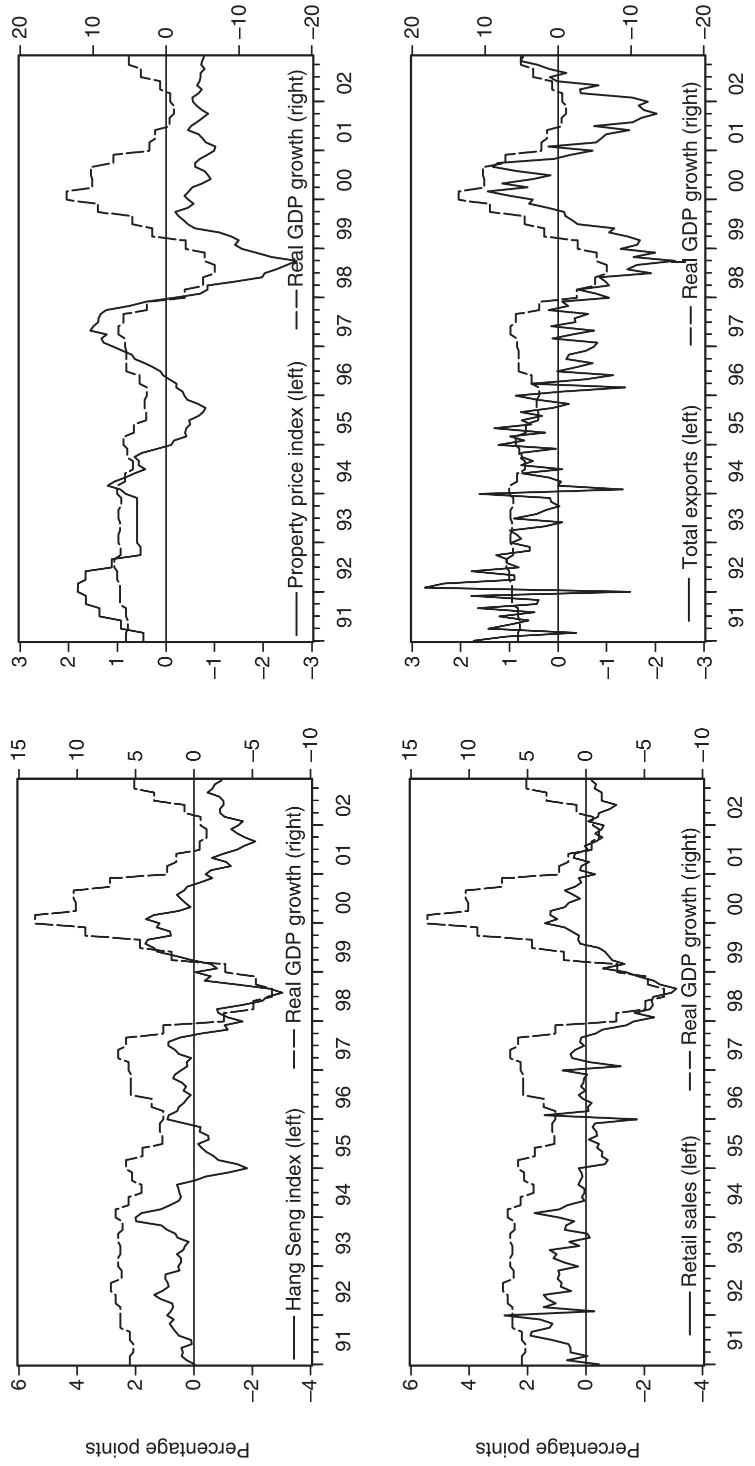

Figure 1. Standardized 12-month growth rates of the four indicator series and four-quarter growth rate of real GDP in Hong Kong, 1990–2002

Table 2. Principal component analysis, sample period January 1991–December 2002

	1st principal component	*2nd principal component*	*3rd principal component*	*4th 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

Note: The principal components are calculated from the correlation matrix of the 12-month growth rates of the four selected indicator series.

than the 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% of the total variation of the four indicators, which suggests that there is an important common component affecting all the series. It also shows the loading of each of the four PCs. The four indicators have similar loadings on the first PC, whereas their loadings on the other three PCs are quite different. In particular, the loadings of the first three variables on the second PC are negative but that of the last variable is positive.

We next explored the common component in these time series by estimating the dynamic factor model proposed by Stock and Watson.[7] Before doing so, we noted that, while related, there are important differences between the PCA and the Stock–Watson methodology. In particular, while PCA essentially provides a compact summary of the co-movements of the time series studied, the latter model permits a structural (in the time-series sense) interpretation of the data. Furthermore, it allows us to conduct formal tests on a wide range of interesting hypotheses, to characterize explicitly the dynamic behaviour of the common component, and to produce formal forecasts with associated confidence bands. It therefore goes much beyond the PCA analysis.

4. THE DYNAMIC FACTOR MODEL

In this section we present the dynamic factor model we used to extract the unobservable common component and to develop a composite coincident index of economic activity in Hong Kong. We first outline the model, then show

[7] In related work, Forni *et al*. (2001) develop a generalized dynamic factor model to extract coincident and leading indicators for the euro area from a large panel of economic variables. Cristadoro *et al*. (2001) apply the same methodology to develop a core inflation index for the euro area.

how it can be written in state–space form and explain how to estimate it using Kalman filtering and maximum likelihood.[8]

4.1. *Specification*

The dynamic factor model can be formulated in terms of the 12-month growth rates of the four indicator variables as follows:[9]

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

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

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

where Y_{1t}, Y_{2t}, Y_{3t} and Y_{4t} denote the logarithms of the Hang Seng index, the residential property price index, retail sales and total exports, respectively, and $\Delta Y_{it} \equiv Y_{it} - Y_{it-12}$. In the above model, ΔY_{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 of order p and q, respectively. For a normalization, the scale of ΔC_t is identified by setting σ_η^2 to unity.

The main identifying assumption in the above model is that the co-movements of the indicator series arise from the single source C_t. In particular, ΔC_t enters the expression for ΔY_{it}, with potentially different weights, γ_i, $i = 1, \ldots, 4$. We further assume that u_{it} and ΔC_t are mutually uncorrelated at all leads and lags.

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, thereby concentrating the D_i and $\gamma_i\delta$ terms out of the likelihood function:

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

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

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

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

As the dynamic factor model written in terms of deviations 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.[10]

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

[9] Since we used the growth rate over 12 months, it was not necessary to seasonally adjust the data.

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

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 and $q = 1$ for u_{2t}, u_{3t}, u_{4t} except u_{1t}, which follows an AR(2) process):

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

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

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

where $[\eta_t \; 0 \; v_{1t} \; 0 \; v_{2t} \; v_{3t} \; v_{4t}]$ 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 above, to estimate the model we formed the likelihood function

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

where T, z_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 maximizing the likelihood function, using the Kalman filter. Doing so, however, requires us to assume initial conditions for the state vector. For stationary models with known parameters, steady-state conditions allow the use of the transition matrix to solve for the initial conditions. However, in our case, since the model parameters have to be estimated simultaneously, we assumed that the prior state vector is a random variable and has a diffuse distribution; that is, its covariance matrix is given by κI with $k \to \infty$ (see Harvey, 1993, p. 88). This is tantamount to assuming that nothing is known about the initial state.

Table 3. Maximum likelihood estimates, sample period January 1991–December 2002

Parameters	*Estimates*	*Asymptotic t-values*
ϕ_1	1.815	115.068
ϕ_2	−0.833	−48.816
d_{11}	1.196	19.184
d_{12}	−0.348	−5.340
d_{21}	0.982	38.050
d_{41}	0.373	4.774
γ_1	0.048	4.504
γ_2	0.053	6.395
γ_3	0.058	6.723
γ_4	0.043	4.384
σ^2_{u1}	0.086	9.541
σ^2_{u2}	0.020	8.416
σ^2_{u3}	0.214	9.559
σ^2_{u4}	0.499	8.559
Log likelihood	−283.251	
Akaike information criterion	4.127	
Hannan–Quinn criterion	4.244	
Diagnostics:	*Test statistic*	*Prob. values*
LB (v_1)	5.094	0.532
LB (v_2)	10.104	0.101
LB (v_3)	4.598	0.596
LB (v_4)	29.112	0.000
JB (v_1)	0.052	0.974
JB (v_2)	8.844	0.015
JB (v_3)	177.100	0.000
JB (v_4)	42.375	0.000

*Not significant at the 5% level.
Note: LB(v_i): Ljung–Box Q test for AR(6) residual autocorrelation; JB (v_i): Jarque–Bera test for normality of the residual series.

5. EMPIRICAL RESULTS

Table 3 presents the estimates of ϕ, γ and the variances of the disturbances in the dynamic factor model for the four indicator series over the sample period January 1991–December 2002.

All parameters are significant at the 5% level. Although the factor loading for total exports is somewhat smaller than those of the other series, as was the case in the PCA, the loadings are broadly similar, implying that all four indicators contain information about the state of the real economy.[11] With regard to the estimated autoregressive coefficients, the roots of $\phi(B)$ lie outside the unit circle and are complex conjugates. Thus, the estimated AR(2) process for Δc_t is stationary and exhibits a cyclical pattern. Since the estimated parameter $\hat{d}_{31}$ for u_{3t} is not significant at the 5% level, the 12-month growth

[11] We have also estimated the model with a subset of indicator series, but found that the resulting coincident indicator was much less correlated with four-quarter GDP growth.

rate of the retail sales series is just the common component, Δc_t plus white noise.

In order to check the adequacy of the model specification, we analysed the standardized disturbances $v_{i,t}$. If the model is well specified and the parameters are known, the residuals $\hat{v}_{i,t}$ should be randomly distributed. In practice, however, the parameters are estimated and the residuals are therefore only approximately random (see Harvey, 1989, p. 256). The randomness can be checked in a number of ways, for instance by performing Ljung–Box tests on the autocorrelations of $\hat{v}_{i,t}$. The results are satisfactory except for $\hat{v}_{4,t}$. Furthermore, we used a Jarque–Bera test to explore the normality of the residuals.[12] Without normality, the Kalman filter will not be the best linear minimum variance estimator. The tests, however, show mixed results. Despite these minor problems, the overall impression is that the model fits the data reasonably well.

Given the estimated parameters, we obtain the unobservable common component by running the Kalman smoother. Figure 2 plots the standardized, estimated common component, Δc_t, against the standardized 12-month growth rates of each of the four indicator series.[13] The unobservable common component evolves over time in a way similar to the first three indicator series, in particular the retail sales series.

To explore how strongly correlated the underlying coincident indicator is with real GDP growth, we adjusted the scale of Δc_t and plotted it against four-quarter GDP growth in Figure 3, with the 95% confidence bands. The contemporaneous correlation between the two series is high (0.86), which even exceeds the correlation between the first PC and GDP growth. Although the model tracks GDP growth reasonably well over the whole estimation period, it suggests stronger economic activity in 1991–92 than evidenced by the real GDP data. This is probably due to the strong speculative activity in the residential property market in the period, particularly in terms of pre-completion sales of flats in major new developments. The coincident indicator also suggests weaker growth in 2000 and stronger growth in 2001 than the real GDP data. It is plausible that these differences may be due to the fact that the model attaches less weight on the service sector than does real GDP data, or that the economy has undergone structural changes in the sample period.

To explore the model further, we next used it to generate one-step-ahead predictions of the unobserved factor for the first nine months in 2003 – that is, out-of-sample. Figure 4 plots the nine one-step-ahead predictions with a 95% confidence band against actual four-quarter GDP growth of the first three quarters of 2003. Overall, the model appears to do a reasonably good job of capturing output fluctuations out of sample.

An attractive feature of the dynamic factor model is that it enables us to construct a composite coincident indicator of economic activity in Hong Kong. However, as the model is fitted in terms of deviations from means, we need to estimate the mean growth rate for the common component ΔC_t. This mean is

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

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

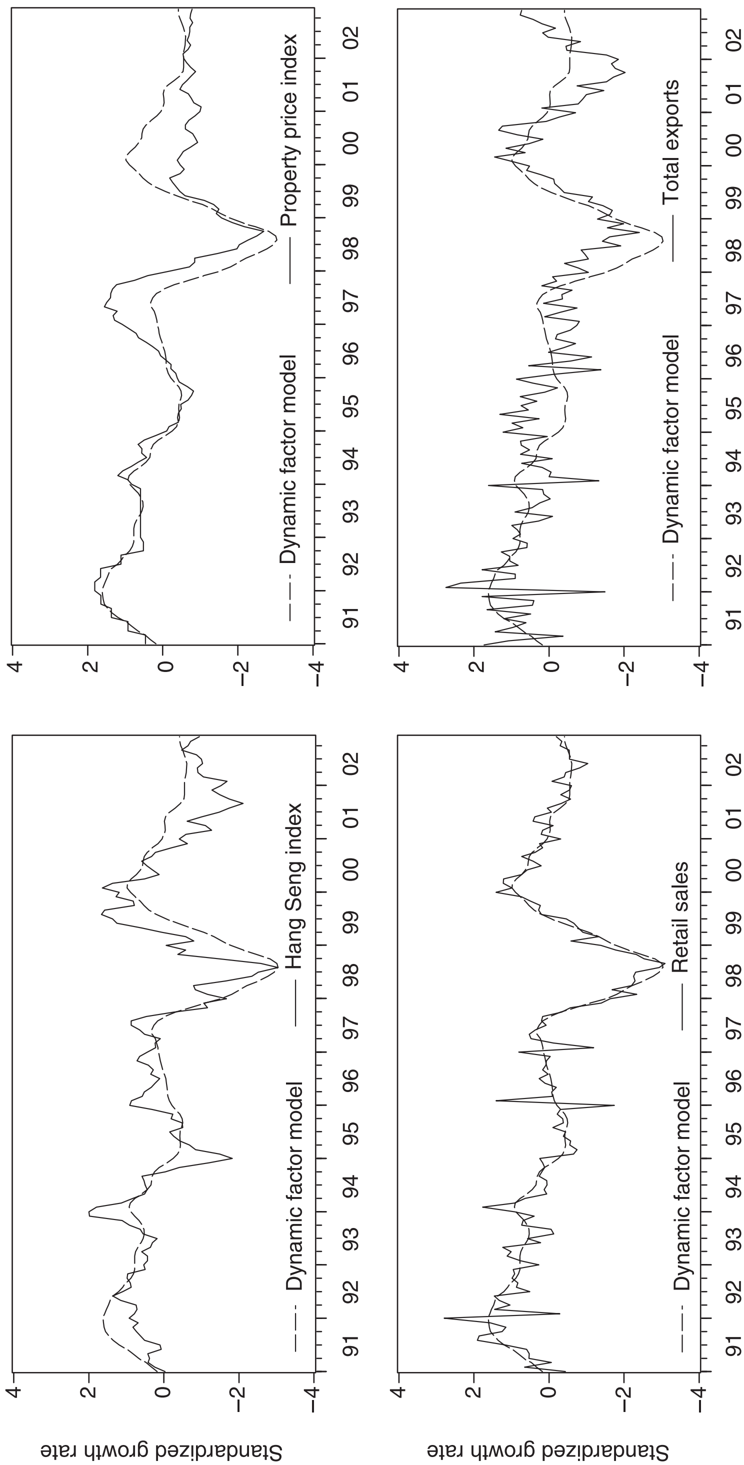

Figure 2. Indicator series and common component, 1990–2002

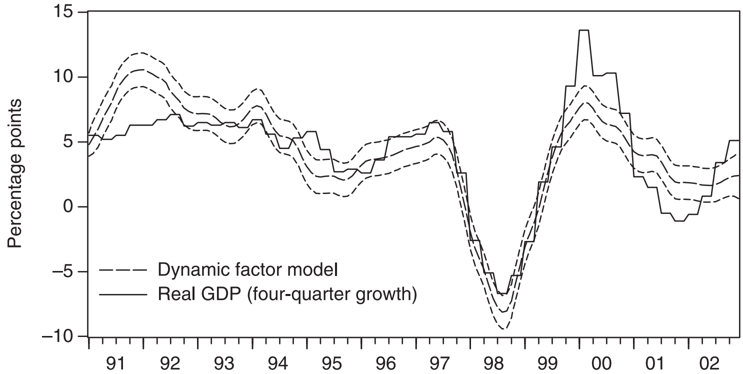

Figure 3. Common component and real GDP (together with 95% confidence band), 1990–2002

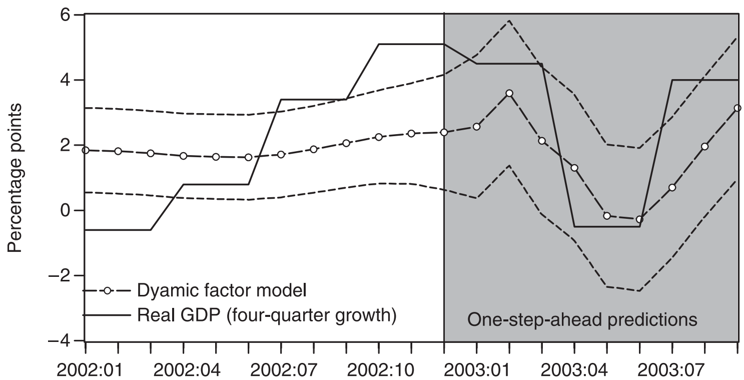

Figure 4. Out-of-sample predictions, January–September 2003

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 were estimated with the Kalman filter algorithm.[14] The estimated, adjusted mean growth rate for ΔC_t is 3.37%. Figure 5 shows the index of coincident indicators of economic activity in Hong Kong. It shows a gradual rise of economic activity from the beginning of 1991 to the middle of 1997 and large swings in the post-1997 crisis period. Whereas the deep recession in 1998 can be easily seen, a less pronounced downturn in 2001 is also readily apparent.

6. CONCLUSION

Since preliminary estimates of GDP in Hong Kong, as in many other economies, are published with a time lag and are subject to revisions, it is of interest

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

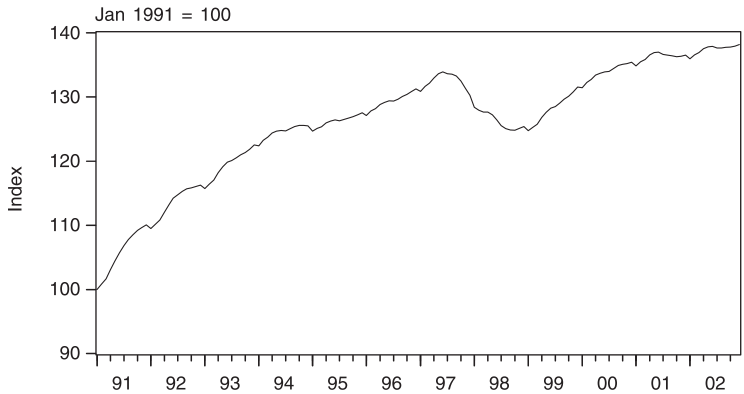

Figure 5. Coincident indicator for Hong Kong, 1990–2003

to explore ways of obtaining (almost) real-time estimates of the state of the real economy. In this paper we have applied the dynamic factor model proposed by Stock and Watson (1989) to do so. Overall, the empirical work suggests that the model is likely to provide a useful tool for assessing economic conditions in Hong Kong.

The research reported on in this paper could be extended in several directions. First, it would be of interest to consider an even broader set of possible indicator variables. Since the Hong Kong economy is highly open, it seems natural to incorporate variables that capture regional economic developments, in particular in Mainland China. Second, an attractive aspect of the dynamic factor model is that it can be used to generate multi-period forecasts with associated confidence bands, and it therefore seems desirable to explore the forecasting ability of the model. Third, the statistical analysis could be extended, for instance by allowing regime switches in the model.[15] This we leave for future work.

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[15] For details, see Kim (1994) and Kim and Nelson (1999).

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