FEATURE ARTICLE

Forecasting the non-rental component of Hong Kong's CCPI inflation – an indicator approach

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This article describes an indicator approach to forecasting the non-rental component of the composite consumer price index (CCPI) inflation for Hong Kong. A large number of monthly indicators are identified and their predictive content for Hong Kong's inflation rate is investigated. Based on certain model selection criteria, four preferred indicator models are chosen and used to forecast the near-term (3-6 months) and short-term (12 months) inflation in Hong Kong.

When added the forecasts of the rental component, these selected indicator models generate a range of headline CCPI inflation forecasts from 1.7% to 2.3% year on year for 2006. These forecasts are generally in line with assessments of the prevailing economic conditions and the forecasts from other models. The performance of these indicator models suggests that they are promising tools in helping improve the accuracy of inflation forecasts for Hong Kong.

I. Introduction

The HKMA has developed a small forecasting model (SFM) to project Hong Kong's output and inflation. The model works well in capturing the turning points in GDP growth and inflation.[1] However, the inflation equation in the SFM using a generalised Phillips Curve approach appears to have a tendency to over-forecast the inflation rate. In the US, the Phillips Curve approach to inflation forecasting has also been found to generate forecasts with large deviations from actual outturns, partly because of the model's inability to accommodate the effect of structural changes both in the short term and the long term (Atkeson and Ohanian, 2001 and Fisher *et al*., 2002). This caveat has since led to new attempts to use an alternative inflation forecasting framework based on a large set of high-frequency economic indicators. After the publication of a seminal paper by Stock and Watson (1999), indicator-based forecast models have gained increased popularity among most major central banks in the world.[2]

As its name suggests, an indicator model assumes that the future rate of inflation depends on one or more currently observed indicators selected on their past ability to forecast inflation developments. Applying this approach has an advantage in that it has largely skirted the issue of structural change because its atheoretical framework does not impose a pre-assumed economic relationship. It can offer more timely forecasts of future inflation developments because the use of monthly indicators allows for more frequent forecast updates. In addition, employing a large set of economic indicators that potentially contains more information on past and future inflation developments should also help improve our forecast accuracy. Notwithstanding

[1] See Ha, Leung, and Shu (2002) and Kong and Leung (2004).

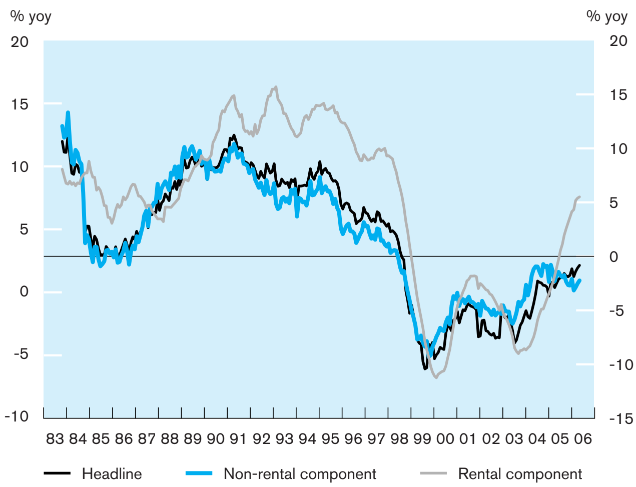
[2] See Brave and Fisher (2004) for the US, Dion (1999) for Canada, Altimari (2001) for the euro area, Bruneau *et al.* (2003) for France, and Kitamura and Koike (2002) for Japan.

these advantages, the indicator approach has problems of its own. First, the indicator selection criteria are often based on statistical properties rather than economic theory, making it difficult to understand the channels through which they affect inflation. Secondly, the composition of indicators to form a best forecast model is often *ad hoc* in nature because the indicators are sensitive to the time period under consideration and the forecast horizons in focus (Fisher *et al*., 2002).

Putting aside these advantages and caveats, we propose a group of indicator models for Hong Kong to forecast the *non-rental component* of the composite consumer price index (CCPI) inflation (Chart 1).[3] The models developed are meant to complement the existing SFM by offering a set of alternative inflation forecasts, which can be used as priors for formulating our views on the inflation outlook, for example when using the SFM.

CHART 1

Composite CCPI and its components



This article proceeds as follows. Section II discusses the methodology of a variety of indicator-based models. Section III presents the forecasting performance of the models developed in section II. Section IV discusses forecast results from a preferred set of indicator models. Section V offers future research directions and concludes.

II. Methodology

Bivariate and multivariate indicator models

The basic indicator-based forecast model takes the form

$$\pi^h_{t+h} - \pi_t = \mu_i + \gamma_i(L)\,\Delta\pi_t + \beta_i(L)D_{i,t} + \varepsilon^h_{t+h} \qquad (1)\ ^{4,5}$$

where $\pi_{t+h}{}^h = (1200\,/\,h)*\log(P_{t+h}\,/\,P_t)$ is the h-period inflation at an annualised rate at time t, with h indicating the forecast horizon and P_t denoting the non-rental component of Hong Kong's CCPI. $\pi_t = 1200*\log(P_t\,/\,P_{t-1})$ is monthly inflation at an annualised rate at date t and $\Delta\pi_t$ is its first difference. $D_{i,t}$ contains one candidate indicator in the case of a bivariate forecasting model and groups of indicators or factors in the case of a multivariate model. $\gamma(L)$ and $\beta(L)$ are polynomials using the lag operator L.

Equation (1) states that h-period ahead inflation can be projected using current and lagged inflation rates as well as a relevant indicator in appropriate lags.[6] Projection horizons of 3 months, 6 months, and 12 months, i.e. h= 3, 6, and 12, are considered in this article for the purpose of forecasting near-term (3-6 months) to short-term (12 months) inflation pressure.[7]

[3] Hong Kong's rental component part of the CPI inflation follows a time pattern of its own and is best forecast using a separate model. These two forecasts can then be combined to obtain a forecast of headline CPI, as illustrated below.

[4] Specification here assumes that inflation follows an I (1) process. Alternative model specifications assuming inflation to be an I (0) process can be written as $\pi^h_{t+h} = \mu_i + \gamma_i(L)\,\pi_t + \beta_i(L)D_{i,t} + \varepsilon^h_{t+h}$ (Sekine, 2001) or $\pi^h_{t+h} - \pi_t = \mu_i + \gamma_i(L)\,\pi_t + \beta_i(L)D_{i,t} + \varepsilon^h_{t+h}$ (Stock and Watson, 1999).

[5] This specification also assumes that inflation and the indicators are not co-integrated.

[6] The advantage of the h-step ahead forecast is that it eliminates the need for estimating additional equations by simultaneously forecasting π_t and $D_{i,t}$ (*e.g.* using a VAR) and therefore reduces the potential effect of specification errors carried over in a typical one-step ahead forecast model (Stock and Watson, 2001).

[7] In general, it is more difficult to use indicators to forecast inflation for a shorter horizon than for a relatively longer horizon. This is because the high level of persistence in inflation will make it difficult to improve upon the simple univariate autoregressive (AR) model.

In addition to the bivariate forecasting model, Equation (1) can be extended to allow for inclusion of multiple indicators or factor(s) – a representation for a group of indicators or even groups of indicators. In principle, more than one economic indicator may contain more information on the future developments of inflation. However, simply including all indicators in the forecast equation would not produce any sensible results either, because of risks of model over-fitting and collinearity of variables. The challenge then involves finding a weighted average of all estimated forecasts or just a principal component derived from a group of indicators that could best reflect the information content of all indicators represented. Two possible approaches have been used in the literature. One is to first use the forecast model as specified in equation (1) and then to select different weighting schemes to combine these forecasts; the other is to extract a factor to first represent useful information from individual indicators and then forecast using equation (1). In this article, we use mean, median, trimmed mean, and a ridge regression method to combine individual forecasts (namely, combination forecast models) and employ principal component analysis to extract information from groups of indicators (leading to the so-called factor model).

Estimation and forecast performance evaluation

The parameters of the model are estimated recursively using ordinary least squares (OLS), which allows us to simulate the actual real-time forecasting by constantly updating the information set. At each stage of the estimation, we choose the number of lags in $\gamma(L)$ and $\beta(L)$ by minimising the Bayesian Information Criterion (BIC) over the full sample.[8] To select the indicators that contain the highest predictive content, we focus on out-of-sample forecasts from January 1998 to March 2006 in which indicator models are recursively estimated with information dated before the forecast period.

The performance of our forecasts is assessed by applying a measure of the averaged magnitude of the forecast error, the root mean-squared error (RMSE). It is defined as $\sqrt{\frac{1}{T_2 - T_1 - h + 1}\sum_{t=T_1}^{T_2-h}\left(\pi_{t+h}^{h} - \hat{\pi}_{i,t+h|t}^{h}\right)^2}$, which measures the standard deviation of the forecast ($\hat{\pi}_{i,t+h|t}^{h}$) from the actual inflation (π_{t+h}^{h}) over the specified forecast sample period while T_1 and $T_2 - h$ are the respective first and last date over which the out-of-sample forecast is computed. Both bivariate and multivariate models are evaluated against the univariate autoregressive model (henceforth, the benchmark) which only uses lagged inflation rate for forecasting. The relative RMSE between an indicator model and the benchmark is considered as our model evaluation criterion. In general, the smaller the relative RMSE, the better performance of the model under consideration.

Candidate Indicators

We select 66 candidate indicators related to the Hong Kong economy, including 50 monthly indicators and 16 quarterly indicators ending in 2006:03.[9] The sample period of our data mostly begins in October 1983, the month when Hong Kong adopted the Linked Exchange Rate System (LERS). These indicator series are subject to a battery of tests on properties of time series.[10] Proper transformations are then implemented accordingly.

[8] We also allow the selection of the optimal number of lags in each estimation step by minimising the Akaike Information Criterion (AIC). Compared with BIC, AIC imposes a smaller penalty for additional lags. In our forecasting exercises, models using the BIC criterion in general produce smaller forecast errors than those using AIC criterion.

[9] The end of regression sample is chosen to be 2006:03 because of publication lags of the quarterly data. The quarterly indicators are converted into monthly ones using interpolation methods.

[10] These tests are mainly concerned with stationarity of the data series which, if not accounted for properly, may lead to spurious in-sample correlations and poor out-of-sample forecasting performance. Details regarding the time series property tests and data transformation are available upon request.

The indicators are broadly divided into the following groups:

(i) the monetary sector group including indicators of monetary aggregates, deposits, and loans (12 series),

(ii) the real sector group covering the labour market, goods market, and output (24 series),

(iii) the financial market and asset price group including indicators on exchange rates, interest rates, stock market indices, and property price indices (17 series),

(iv) various price indicators including commodity prices, import, and export prices (6 series), and

(v) US related indicators including US CPI, capacity utilisation rate, unemployment rate, and measures of interest rates and term spread[11] (7 series).

III. Forecast performance

Bivariate models

We first apply the bivariate model to investigate the predictive content of each indicator on Hong Kong's *non-rental component* CCPI inflation. Based on the relative RMSE, we draw the following conclusions:[12]

- Our results appear to suggest that indicators from the real and financial sectors have more predictive power in forecasting inflation in Hong Kong than those from the monetary sector, contrary to results found elsewhere. This could be partly due to Hong Kong's unique monetary arrangement as the money supply is not driven by monetary policy, but is endogenously determined.

- It appears that the longer the forecast horizon, the more the indicators outperform the benchmark. In addition, there is a sectoral dimension to this observation. That is, the number of useful indicators from certain sectors rises significantly as the forecast horizon increases. For example, at the 6-month horizon, various Hong Kong interest rates start to outperform the benchmark. At the 12-month horizon, exchange rate indicators start to outperform, while the performance of the interest rates improves further. This finding is consistent with the observation that certain policy rates and exchange rates often have a lagged effect on the economy and, therefore, inflation.

- Although we expect indicators to have different predictive powers at different forecast horizons, there appear to be 10 indicators (mostly in the real and financial sectors) that outperform the benchmark across all forecast horizons. In particular, indicators reflecting labour market conditions appear to contain high predictive content about Hong Kong's inflation, with the single most useful indicator being the job vacancy indicator, which has the highest predictive power among all indicators and across all forecast horizons.

Overall, our bivariate forecasts appear to improve the benchmark for a number of indicators across different sectors and forecast horizons. The findings also help serve as a guide for selecting and combining indicators for the multivariate models.

Multivariate models

In connection with the findings from the bivariate forecasts, we offer the following observations from the multivariate models that use either a combination of forecasts (denoted as a combination forecast model) or a combination of indicators (denoted as a factor model).

[11] In theory, the LERS implies that inflation in Hong Kong will be subject to significant influence from the US economy. Genberg and Pauwels (2002) also looked at US CPI in their study of inflation in HK. They found no single individual country's CPI (*e.g.* US CPI) could sufficiently represent the external influence on HK's inflation.

[12] To save space, the forecast performance of individual indicators and groups of indicators are not discussed here.

- Multivariate models do not always outperform the benchmark, especially at shorter forecast horizons. However, when they do, they often outperform the benchmark and most of the bivariate models by a considerable margin. This suggests that using multivariate models provides extra information and could improve the forecast accuracy.

- It appears that simply employing more indicators does not necessarily improve the forecast performance of multivariate models. However, when these models are based on information from certain sub-sectors, they provide us with better forecast performance, for example models for the labour market sector and for a pre-selected group of indicators.

- While factor models have the highest ability to forecast at all three forecast horizons using the labour market indicators, combination forecast models tend to outperform factor models for some other groups of indicators. In addition, our results suggest that mean or trimmed mean forecasts perform better than the median forecasts, contrary to results obtained from other economies.

IV. Applying the indicator models to forecast Hong Kong's inflation

We select four preferred models based on the model-selection criterion, relative RMSE to the benchmark autoregressive model. Out of the bivariate models, we select a model using the job vacancy indicator. From the group of multivariate models, we select a factor model, a combination model based on trimmed mean and ridge regression,[13] each using a group of labour market indicators and a group of pre-selected indicators.

Table 1 reports the averaged year-on-year inflation forecasts for the *non-rental component CCPI* using data ending March 2006. Columns labelled under June, September and December correspond to forecasts applying forecast horizons of 3, 6, and 12 months respectively.[14] Note that the figures in the table are all on an averaged year-to-date basis. The

TABLE 1

Projected non-rental component of the CCPI inflation rate (year-on-year percentage change)

Time Period (Forecast Horizon)	**June** (3 months ahead)	**September** (6 months ahead)	**December** (12 months ahead)
Univariate (benchmark)	0.36	0.26	0.60
Bivariate			
Job Vacancy	0.48	0.52	1.61
Multivariate			
Labour market indicators			
Comb. Ridge Regression	0.45	0.34	0.98
Comb. Trimmed Mean	0.42	0.34	0.82
Factor Model	0.38	0.33	1.37
All indicators that outperform the benchmark			
Comb. Ridge Regression	0.43	0.33	0.83
Comb. Trimmed Mean	0.38	0.29	0.69
Factor Model	0.40	0.24	0.71

Note: Figures are on a year-to-date basis.
Source: Staff estimates.

[13] When the problem of multi-collinearity occurs, OLS estimators remain unbiased but with large variance. Ridge regression attempts to trade some unbiasedness for the reduction of variance so that the estimators are more accurate.

[14] For the 2006 forecasts, we are able to utilise the data available till March 2006. One of the purposes of applying forecast horizons of 3, 6, and 12 months for inflation forecasts, made up to June, September and December respectively, is to maximise the use of the available data.

bivariate model using the job vacancy indicator provides us with a set of forecasts of 0.5%, 0.5% and 1.6% respectively, for the three specified forecast horizons. When compared with the bivariate forecasts, the multivariate models predict only modest increases in inflation for the year to September and December, in a range of 0.2%-0.3% and 0.7%-1.4% respectively; while the range of inflation rates for the first half of the year projected by the multivariate models is similar to that produced by the bivariate model.

Adding the forecasts of the rental component segment estimated separately,[15] we obtain the forecast *headline* CCPI inflation rates, averaged year-on-year, in the range of 1.6% for H1 2006, 1.5%-1.7% for the year to September, and 1.7%-2.3% for 2006 as a whole (Table 2). Table 3 compares our forecasts for 2006 as a whole with those obtained from other models and other forecasters.[16]

TABLE 2

Projected averaged headline inflation rate (year-on-year percentage change)

Time Period (Forecast Horizon)	**June** (3 months ahead)	**September** (6 months ahead)	**December** (12 months ahead)
Univariate (benchmark)	1.55	1.49	1.59
Bivariate			
Job Vacancy	1.64	1.68	2.33
Multivariate			
Labour market indicators			
Comb. Ridge Regression	1.61	1.55	1.87
Comb. Trimmed Mean	1.59	1.55	1.75
Factor Model	1.56	1.54	2.15
All indicators that outperform the benchmark			
Comb. Ridge Regression	1.60	1.54	1.75
Comb. Trimmed Mean	1.56	1.51	1.65
Factor Model	1.58	1.47	1.67

Note: Figures are on a year-to-date basis.
Source: Staff estimates.

TABLE 3

2006 Headline inflation forecasts from various sources

	2006 (in %)
Indicator Models (HKMA)	**1.7-2.3**
Small Forecast model (HKMA)	2.3
Government Forecasts	2.3
Consensus Forecasts (Jul-06)	2.2

Source: HKMA, Census & Statistics Department and Consensus Forecasts.

[15] This is estimated using a univariate autoregressive model applying the monthly market rental index series. As Hong Kong's rental component has a weight of 26.4% in the CCPI, the headline inflation is then calculated using a weighted average of the non-rental component and the rental component of the CCPI.

[16] Note that these numbers are calculated based on 12-month ahead inflation forecasts.

V. Conclusion

We use a bivariate model to examine 66 indicators individually and find that a number of them outperform the benchmark univariate autoregression model and some by a considerable margin. We find that although multivariate models do not always perform better than the benchmark, when they do, they usually improve upon both the benchmark and most of the bivariate forecasts. These results suggest that both bivariate and multivariate models are useful alternative models to forecast inflation.

We select four preferred indicator-based models to conduct inflation forecasts for 2006. The headline CCPI inflation forecasts produced by these models are in the range of 1.7% and 2.3%, which are comparable to, but slightly lower than, those projected from other models. As these forecasts are purely model generated, they can be treated as one of our priors for formulating our views on future inflation developments, particularly when applying the HKMA small forecast model.

Although still at an early stage of development, these indicator-based models appear to be promising tools in improving our understanding of Hong Kong's inflation process. Sensitivity analysis can be conducted by employing a broader group of indicators that may have a shorter time span than those employed in the current models. Finally, the forecasts presented here are meant for illustrative purposes and do not represent the official inflation forecasts of the HKMA.

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