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# *FORECASTING THE NON-RENTAL COMPONENT OF HONG KONG'S CCPI INFLATION – AN INDICATOR APPROACH*


***Key points:***

- *This paper develops both a bivariate and a multivariate indicator model using a large group of high-frequency economic indicators to forecast Hong Kong's non-rental component inflation. Indicator models can offer timely forecasts on future inflation developments because monthly indicators are often employed, thus allowing more frequent updates of forecasts.*

- *We first apply the bivariate model to investigate the predictive content of 66 indicators and find that quite a number of them have high predictive content for inflation forecast. In particular, indicators from the real and financial sector have more predictive power than those from the monetary sector, partly owing to Hong Kong's unique monetary arrangement.*

- *We then apply the multivariate model to examine the predictive content of groups of combined forecasts and indicators. Our results suggest that combining individual forecasts or individual indicators adds additional information and can help improve the forecast accuracy of Hong Kong's inflation by a considerable margin.*

- *Three preferred indicator models are employed to forecast the near-term (3 to 6 months) and short-term (12 months) inflation for non-rental component of the CCPI in Hong Kong. These models generate a range of averaged year-on-year inflation forecasts from 1.6% to 2.4%, which is in line with our assessments of the prevailing economic conditions.*

- *Though at an early stage of development, the performance of these models suggests that they are quite promising tools to help improve the accuracy of our inflation forecast. Specifically, the forecasts derived from these indicator models can be used as priors for formulating our view on future inflation developments in Hong Kong.*



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## I. INTRODUCTION

The Phillips Curve model has played an important role in inflation forecasting. While it does a reasonably good job in capturing turning points of inflation developments, it often generates inflation forecasts of large deviations from actual turnouts owing to its 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). Furthermore, the Phillips Curve approach was found to underperform a naïve forecast, *i.e.*, one in which inflation over the next forecast period, say one year, will be the same as it has been over the last four quarters (Lansing, 2002). These drawbacks have since led to new attempts to use an alternative method to forecast inflation. After the publication of a seminal paper by Stock and Watson (1999), an indicator-based inflation forecast model has gained increased popularity among most major central banks in the world.[1]

The indicator approach to forecasting inflation has the advantage in that it has largely skirted the issue of structural change because of its atheoretical framework which does not impose a pre-presumed economic relationship. It can offer more timely forecasts on future inflation developments because monthly indicators are often employed, thus allowing more frequent updates of forecasts. In addition, employing a large set of economic indicators that potentially contains information on past and future inflation developments should help improve our forecast accuracy. Nevertheless, it also has problems of its own. First, the indicator selection criteria are often based on statistical properties rather than economic theory. Therefore, it is difficult to understand the channels through which they affect inflation. Second, 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 in consideration and forecast horizons in focus (Fisher *et al.*, 2002).

This paper adopts the indicator approach using Hong Kong's high-frequency (monthly) data to forecast the non-rental component of the composite consumer price index (CCPI) inflation.[2] The objectives of the

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1 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 (2003) for Japan.

2 Hong Kong's rental component part of the CPI inflation follows a time path of its own and must therefore be forecasted using a separate model.

paper are threefold: First, it attempts to identify a large number of high-frequency indicators of inflation and use them to obtain out-of-sample forecasts so as to investigate their predictive content for Hong Kong's inflation rate. Second, it introduces a set of indicator-based forecast models and evaluates their relative performance based on a set of model selection criteria. Third, models developed in this paper could complement the existing small macroeconomic forecast model based on a generalized Phillips Curve model[3] and offer a set of alternative inflation forecasts. Ultimately, the aim of this research is to provide a more accurate assessment of both the direction and magnitude of future inflation developments for purposes of better policy formulation and risk management under the Linked Exchange Rate System (LERS).

The paper proceeds as follows: Section II adopts the Stock-Watson (1999) model with variations to forecast inflation using high-frequency indicators. Section III discusses the properties and the transformations of the data used. Section IV presents forecasting results based on the bivariate and multivariate models. Section V provides a range of non-rental component inflation forecasts from a set of preferred indicator models. Section VI concludes and identifies future directions of the research.

## II. METHODOLOGY

Following the analytical framework developed by Stock and Watson (1999, 2003), we consider both bivariate forecasting models based on a single indicator and multivariate forecasting models based on indicator groups.

### *II.1 The Basic Model*

The basic indicator-based forecast model takes the form

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

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[3] See Ha, Leung, and Shu (2002). The model applies an error correction method and employs GDP gap, rather than, unemployment rate, to forecast Hong Kong's inflation.

[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 $\pi_{t+h}^{h} = \mu_i + \gamma_i(L)\pi_t + \beta_i(L)D_{i,t} + \varepsilon^{h}{}_{t+h}$ (Sekine, 2001) or $\pi_{t+h}^{h} - \pi_t = \mu_i + \gamma_i(L)\pi_t + \beta_i(L)D_{i,t} + \varepsilon^{h}{}_{t+h}$ (Stock and Watson, 1999).

[5] This specification also assumes that inflation and the indicators are not cointegrated.

where $\pi_{t+h}{}^{h} = (1200/h)*\log(P_t / P_{t-h})$ 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 the Hong Kong 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[6], while $\gamma(L)$ and $\beta(L)$ are polynomials using the lag operator $L$. μ is a constant and $\varepsilon^{h}{}_{t+h}$ is forecast error that follows standard properties.

Equation (1) states that $h$-period ahead inflation forecast can be projected using current and lagged inflation rates as well as a relevant indicator in appropriate lags.[7] Projection horizons of 3 months, 6 months, and 12 months, *i.e.*, h= 3, 6, and 12, are considered in this paper for the purpose of forecasting near-term (3 to 6 months) to short-term (12 months) inflation pressure. In general, it is more difficult to use indicators to forecast inflation for a near term 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 contrast to traditional regression methods of estimating over the full sample, our estimation method is based on recursive ordinary least squares (OLS) where more data are used when the forecasting is moving forward in time. This method allows us to simulate more closely the actual real-time forecasting by constantly updating information sets. Specifically, consider an inflation forecast of h-month ahead at date t with h being six and t starting from 1998:01. To obtain the 6-month inflation rate for the period 1998:01 – 1998:07, equation (1) is estimated using data through 1998:01 and a forecast is made based on the estimated coefficients. Next, moving forward one month, the model is re-estimated using data through 1998:02 and another forecast is produced for the inflation over 1998:02 – 1998:09. At each step, one forecast of a 6-month inflation rate is generated and this process is repeated forward. Note that our empirical

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6 As discussed in the next section, when $D_{it}$ contains groups of indicators, equation (1) is referred as a multivariate model.

7 The advantage of the h-step ahead forecast is that it eliminates the need for estimating additional equations by simultaneously forecasting $\pi_t$ 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).

analysis focuses on out-of-sample forecasts in that all models are estimated with data dated before the forecast period.

At each stage of the estimation, we choose the number of lags in $\gamma(L)$ and $\beta(L)$ by minimizing the Bayesian Information Criterion (BIC) over the full sample.[8] The length for the distributed lags is allowed to vary between zero and eleven. Since the recursive OLS requires the model to be re-specified and estimated at each date, the restrictions on lag lengths of both polynomials are assumed to be the same in order to ease computational burden.

The performance of an indicator-based forecast is assessed by applying a measure of the average magnitude of the forecast error, the Root Mean-Squared Error (RMSE), which measures the standard deviation of the forecast from the actual inflation over the specified forecast sample. It is defined as $\sqrt{\frac{1}{T_2 - T_1 - h + 1}\sum_{t=T_1}^{T_2-h}\left(\pi_{t+h}^{\ \ h} - \hat{\pi}_{i,t+h|t}^{\ \ h}\right)^2}$, the square root of the average of the squared differences between the actual inflation and the projected inflation based on indicator $i$ ($\hat{\pi}_{i,t+h|t}^{\ \ h}$), where $T_1$ and $T_2 - h$ are the respective first and last dates over which the out-of-sample forecast is computed. In general, the RMSE of a univariate AR model is chosen as the benchmark (henceforth, the AR model is used interchangeably as the benchmark) against which the performance of a candidate forecast is evaluated.[9]

### *II.2 Multivariate Forecasting Models*

Besides 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, many economic indicators may contain some information on the past, current, or future developments of inflation. But simply including all indicators in the forecast equation would not produce any sensible results either, because of risks of model overfitting and collinearity of

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8 We also allow the selection of the optimal number of lags in each estimation step by minimizing the Akaike Information Criterion (AIC). Compared to 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 univariate AR model is defined as equation (1) without the lag polynomial of indicator $D_{i,t}$.

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 information content of all indicators represented. Two possible approaches have been used in the literature. One is to first estimate the forecast model as specified in equation (1) and then to use different weighting schemes to combine these forecasts; the other is to use a factor to first represent useful information from individual indicators and then use it to do forecast using equation (1). In this paper, we employ both approaches.

*II.2.a Combination forecast models*

Combining forecasts estimated from different indicators employs more information and therefore should in theory be more efficient than any individual forecasts. In fact, encouraging results applying this approach have been found in many previous studies, notably, Stock and Watson (1999, 2003), Leigh and Rossi (2002), and Marcellino et al (2003). The combined forecasts estimated at time *t* can be constructed as a weighted average of the individual forecasts

$$f_{c,t} = \sum_{i=1}^{n} \omega_{i,t} f_{i,t} \tag{2}$$

where $f_{i,t} = \hat{\mu}_i + \hat{\gamma}_i(L)\Delta\pi_t + \hat{\beta}_i(L)D_{i,t}$ is a forecast derived from equation (1) using a single indicator in $D_{i,t}$. The theory on the optimal linear forecast combination (Bates and Granger (1969), Granger and Ramanathan (1984)) suggests that the theoretically derived optimal weights should correspond to the coefficients $\omega_{i,s}$ (*s = 1 …, t*) in a regression where the true future value $(\pi_{t+h}{}^{h} - \pi_t)$ is regressed on the various forecasts as in equation (3):

$$\pi^{h}_{s+h} - \pi_s = \sum_{i=1}^{n} \omega_{i,t} f_{i,s} + \varepsilon^{h}{}_{s+h} \qquad s = 1,...,t \tag{3}$$

In practice, however, OLS estimation of equation (3) generally produces poor results, owing to a relatively large number of individual forecasts presented in the forecast equation and the possibility of serious multi-collinearity problem among them. We therefore consider estimators derived from a modified ridge regression[10] defined by equation (4) (Stock and Watson, 1999 and Chan, *et al.*, 1999):

$$\widehat{\omega}_{t,RR} = \left( cI_n + \sum_{s=1}^{t} F_s F_s' \right)^{-1} \left( \sum_{s=1}^{t} F_s \left( \pi^h{}_{s+h} - \pi_s \right) + c/n \right) \qquad (4)$$

where $F_s = \left( f_{1,s} \cdots f_{n,s} \right)'$ and $c = k * TR\left( n^{-1} \sum_{s=1}^{t} F_s F_s' \right)$. Parameter k governs the amount of trade off between variance and unbiasedness of an estimator.[11] Following Stock and Watson (1999), we report results based on k = 1, which corresponds to shrinking the OLS estimator half way to the equal weighted value of 1/n.

As discussed in Stock and Watson (2003) and others, an intriguing finding in the literature is that forecasts computed based on theoretically and optimally estimated weights often do not perform as well as those using weights based on simple means or medians of forecasts.[12] We therefore also compute forecasts based on 1) sample mean, that is, $\omega_{it} = \frac{1}{n}$ so $f_{c,t}$ is the sample mean of forecasts at the date t; 2) sample median, that is, $f_{c,t}$ is less influenced by outliers of forecasts; and 3) trimmed mean, that is, the mean of a sample that is already rid of outliers.

### *II.2.b Factor model based on principal component analysis*

In contrast to combining information contained in individual *forecasts*, another method is to allow the forecast model to incorporate information (from a group of indicators) *before* making forecast. The idea behind this approach is that there is some common component of the indicators that could be useful in predicting inflation. This common or principal

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[10] 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. Parameter k is determined from the optimal trade-off between the degree of unbiasedness and the amount of variance reduction. Using ridge regression often gives better out-of-sample predictive power for the forecasts (Chan, Stock and Watson (1998), Stock and Watson (1999)).

[11] Ridge regression technique entails shrinkage towards a pre-specified parameter vector (generally unknown). In practice, k =0.1, 0.25, 0.5, 1 and 10 are usually chosen. When k=0, $\widehat{\omega}_{t,RR} = \widehat{\omega}_{t,OLS}$, as k grows large, $\widehat{\omega}_{t,RR} \to 1/n$.

[12] Stock and Watson (2003) suggested that simply averaging the forecasts from a very large number of models gives the best predictive performance of inflation (and output growth), and this is consistent across sub-forecast periods and across countries.

component can then be used to replace $D_{it}$ in Equation (1) directly. According to Stock and Watson (1998), the principal component method, under the fairly general conditions, also produces consistent estimators out of a group of indicators.[13]

## III. DATA

### *III.1 Description and Transformation*

The sample period of our data mostly begins in October 1983, the month when Hong Kong adopted the LERS. We collected 84 candidate indicators related to the Hong Kong economy, including 67 monthly indicators ending in 2005:12[14] and 17 quarterly indicators ending in 2005:9.[15] The quarterly indicators are converted into monthly ones using interpolation methods. After excluding data that have a short period of coverage, i.e., excluding those available only since 1991, we use the remaining 66 variables for the forecast exercises.

These 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

[13] The first principal components, estimated as the highest eigenvalues from the eigenvector of the group of indicators, explain the largest variation in the data.

[14] The monthly data is available at different time. Some are released at the same time as the CCPI, some lag one month (e.g. retail sales and unit value index of imports) while financial market data are available one month ahead of the CCPI.

[15] The end of regression sample is chosen to be 2005:09 because of publication lags of the quarterly data.

(v) US related indicators including US CPI, capacity utilization rate, unemployment rate, and measures of interest rates and term spread[16] (7 series).

We then apply some conventional transformations to the raw data. First, all series are adjusted for their seasonality, using the X-12 additive method created by the US Bureau of Census, except for interest rates, exchange rates, stock prices, non-fuel commodity prices, and foreign exchange reserves. These seasonally adjusted indicators are then re-scaled in logarithm with the exception of those variables that are negative or are already measured in changes such as interest rates, unemployment rates, output gap, and inventory investment. A complete list of data together with their grouping, description, coverage, frequency, and the type of transformation performed is presented in Table 1.

### *III.2 Time Series Property Tests*

Next, we perform standard tests on the time-series properties of all indicators and the results are presented in Table 2. Unit root tests on the transformed series are conducted using both the Augmented-Dickey-Fuller (ADF) and Phillip-Perron (PP) tests. Most variables appear to contain at least one unit root in one of the two tests, so we take first or second differences to obtain stationarity. In view of the uncertainty of unit root tests against the alternative hypothesis of stationarity, our choice of whether to use a particular order of differencing a time series in question is based on both judgement over test results and conventions used in the literature.[17]

In some cases, we consider the use of more than one transformation for certain indicators. For example, interest rates and unemployment rates are modelled as both I (0) and I (1) series, while nominal wage and payroll are modelled as both I (1) and I (2) series. This then gives us a maximum of 85 potential indicators. In addition, there is some ambiguity in the literature about the order of integration of the CPI series. The ADF test suggests that the non-rental component of the

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[16] In theory, the LERS implies that inflation in Hong Kong will be subject to significant influence of 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.

[17] For example, we follow convention and model the US capacity utilization as an I(0) process.

Hong Kong CCPI inflation follows an I (2) process while the PP test indicates that it follows an I (1) process. We therefore consider both modelling assumptions in our regression.[18]

Additional in-sample tests are conducted to help assess statistical relationship between a candidate indicator and inflation. We perform a bivariate Granger causality test, a bivariate VAR analysis with impulse response functions, and correlations analysis between each indicator and inflation.[19] These exercises are informative in identifying a potential causal relationship and/or the lead or lag structure of various indicators. Results from the Granger causality tests suggest that at a 10% (5%) significance level, 24 (13) variables appear to provide additional explanatory power in forecasting inflation. These variables are highlighted in Table 2.

Although in-sample tests are necessary steps towards evaluating the predictive content of an indicator, Stock and Watson (2001, 2003) point out that in some cases, significant in-sample statistics (e.g. from the Granger causality test) may contain little or no information on whether these indicators have been a reliable predictor for forecasting. We thus turn our attention more to discuss the out-of-sample forecasting properties of the candidate indicators.

## IV. OUT-OF-SAMPLE FORECAST RESULTS

### *IV.1 Bivariate Inflation Forecasts*

#### *IV.1.a Average out-of-sample forecast performance over 1998 – 2005*[20]

Table 3 summarises the forecasting performance of 66 indicators over the period of 1998:1 – 2005:9.[21] To facilitate comparison, we compute relative RMSEs (denoted as "Rel. RMSE" in the Table), which is defined as

[18] In our sample, the forecasts appear to be more accurate using the I (2) specification, so only the results obtained based on this transformation are reported in this paper.

[19] To save space, we report only the results from the Granger causality tests and contemporaneous correlations.

[20] Our forecasting period is chosen to start after the outbreak of the Asian financial crisis.

[21] For variables with more than one transformation, we report the one with better forecast performance.

$$\sqrt{\frac{1}{T_2 - T_1 - h + 1}\sum_{t=T_1}^{T_2-h}\left(\pi_{t+h}{}^{h} - \hat{\pi}_{i,t+h|t}{}^{h}\right)^2} \Bigg/ \sqrt{\frac{1}{T_2 - T_1 - h + 1}\sum_{t=T_1}^{T_2-h}\left(\pi_{t+h}{}^{h} - \hat{\pi}_{AR,t+h|t}{}^{h}\right)^2} \quad ,$$

that is, a ratio between estimated RMSEs of the bivariate forecasts ($\hat{\pi}_{i,t+h|t}{}^{h}$) and that of the benchmark univariate AR forecasts ($\hat{\pi}_{AR,t+h|t}$). A ratio less than 1 indicates that the bivariate forecasts has smaller averaged RMSEs, implying the bivariate model on average outperforms the benchmark.[22] Those outperforming indicators are highlighted in bold and signs of "*" and "**" indicate a reduction of RMSE between 5% and 10%, and above 10%, respectively.

Several observations can be drawn from the results of the bivariate forecasts: First, it appears that the longer the forecast horizon is, the more indicators that outperform the benchmark. Specifically, as the forecast horizon increases from 3 to 6 and 12 months, the number of outperforming indicators also increases from 16 to 24 and 26. Furthermore, there is a sectoral dimension to this observation. That is, the number of indicators from certain sectors such as the group of financial sector and asset prices rises significantly as the forecast horizon increases. For example, at 6-month horizon, various HK interest rates (1-month and 3-month interbank offer rates and HK$ time deposit rates) start to outperform the AR model. At 12-month horizon, exchange rate indicators (nominal and real effective exchange rates) start to outperform, while the performance of the interest rates improves further. In particular, the real effective exchange rate index with a declining weight of the renminbi exhibits an impressive gain of 11% in terms of relative RMSE. In addition, there are also cases where some indicators appear to perform better only at certain forecast horizon. For example, real private consumption expenditure appears to have a high forecastability at a horizon of 6 months, improving the AR model by 6% while it underperforms the benchmark by 2% at forecast horizons of 3 months. Similarly, the monthly Hang Seng Index measured by the price and earning ratio performs better only at 6-month forecast horizon than other indicators.

[22] In the current version of the paper, we rely on the point estimates of RMSEs to provide a ranking of the competing forecasting models. Note that there are potentially sampling errors associated with the relative RMSEs. We will report the test results on the null hypothesis that the relative RMSE is one versus the alternative hypothesis that it is less than one, based on McCracken (1999) and Clark and McCracken (2001), in a later version of the paper.

Second, although we expect indicators to have different predictive contents at different forecast horizons, it is noted that some indicators appear to outperform consistently across all forecast horizons. These include two measures from the monetary indicator group (Hong Kong Dollar M1 and Total M1), eight indicators from the real sector group (job vacancy, nominal payroll index, value and volume indices of retail sales, total trade, total imports, total exports, output gap, and gross domestic product at constant price), three measures in the group of financial sector and asset price (Hang Seng index, the Hang Seng index P/E ratio, and the best lending rate) and one indicator in the group of prices (the world primary commodity price excluding fuel). Out of these indicators, job vacancy has the smallest RMSEs across 3-, 6-, and 12-month forecast horizons by improving over the benchmark by 10%, 22%, and 26%, respectively. Somewhat to our surprise, real gross domestic product also performs quite well as it improves over the benchmark AR forecasts by 2%, 10% and 14%, for respective forecast horizons of 3, 6 and 12 months.

Third, consistent with the findings of other studies, our bivariate model confirms that the unemployment rate does not appear to perform particularly well relative to other indicators. In fact, the indicator underperforms the AR model on all occasions, thus casting doubt on its reliability and accuracy for inflation forecasts when applying the Phillips Curve model. Perhaps partly owing to this problem, output gap is employed to forecast the inflation rate for Hong Kong in the Small Macroeconomic Forecasting Model. Although it marginally outperforms the benchmark in our indicator-based analysis, the GDP gap performs poorly relative to other outperforming indicators, particularly when compared with that of job vacancy.

Fourth, our results appear to suggest that indicators from the real and financial sector have a more predicative power in forecasting inflation in Hong Kong than those from the monetary sector. This could be partly owing to Hong Kong's unique monetary arrangement as money supply is not driven by monetary policy but is endogenously determined. This is in contrast with other studies. For example, using a similar approach, Altimari (2001) found that monetary aggregates provide high predictive content for the euro area inflation.

Finally, it is worth noting that some indicators that have previously been identified as rather informative in explaining Hong Kong's inflation, for example, the unit value index of imports (Genberg and Pauwels, 2002), do not appear to have a strong out-of-sample forecasting power according to our results.

Overall, our bivariate forecasts appear to obtain a reduction of RMSEs relative to the benchmark case for quite a number of indicators across different sectors. This helps to serve as a guide for selecting indicators for the multivariate models.

*IV.1.b Indicator stability over 1998 - 2005*

It is often observed in the literature (Fisher et al. (2002, 2004)) that indicators that do well in some periods could do poorly in others. Therefore, simply averaging the RMSEs over the whole out-of-sample forecast period may not fully reveal the information content of the indicators at different sub-periods. Simply put, an indicator that outperforms the AR model on average may not do so consistently in all sub-periods.

We follow Cecchetti et al. (2000) and Marcellino et al. (2003) by dividing the out-of-sample forecast period into equal length of 7 sub-periods, with each being 24 months long and the first 12 months of the current forecast sub-period overlapping with the last 12 months of the preceding sub-period. The sub-periods start from 1997:10 to 1999:9 and extend to 2003:10 to 2005:9. We compute the corresponding RMSEs for individual indicators in each sub-period and then compare them with those of the AR model. Table 4 reports the number of indicators that outperform the AR model and also identifies the indicators with the lowest RMSEs in each sub-period. To save space, we focus on results for 6–month ahead forecasts.

Columns 2 and 3 in Table 4 reveal that the proportion of indicators that outperforms the benchmark varies considerably, fluctuating between 14% and 68% across the seven sub-periods.[23] It appears that

[23] This is consistent with results in Cecchetti et al. (2000). In their 8-quarters ahead forecast for US inflation over 1985–1998, Cecchetti et al. found the indicator-based forecasts in general performed worse than the AR model in the 13 sub-forecast periods considered and the best indicator outperformed the autoregression only marginally in some periods.

there is a sharp drop of outperforming indicators between October 2000 and September 2003. Consistent with the findings from the whole sample analysis, the sub-sample results also suggest that on average the bivariate forecasts perform worse than the benchmark. Nevertheless, for each sub-forecast period, we can always find some better indicators that can outperform and sometimes by a sizable margin. In particular, job vacancy stands out as the best overall one, outperforming the benchmark as well as all others predictors in four out of the seven sub-sample periods. While unemployment rate performs the best during the economic downturn period between 1997 and 1999, the real effective exchange rate and inventory indicators appear to have more predictive power than others during the period from 1999 to 2002 when the economy stagnated.

Table 5 ranks the performance of each indicator relative to the AR model in a descending order. Note that only indicators that outperform the AR model (indicated by symbol "*") for at least one sub-period are included. It can be shown that there are 16 indicators outperforming the AR model in more than four out of the seven sub-samples. Among them, all but one (US interest rate spread) outperform the benchmark over the whole sample period between 1998 and 2005 (Table 3).

Not reported here, sub-sample analyses are also conducted for forecast horizons of 3 and 12 months. The results are similar to that of 6-month ahead forecast. Though job vacancy still outperforms others in 3 to 4 sub-periods out of the seven sub-sample periods, a different set of better performing indicators also emerged. For example, while the monthly rental index of residential property performs the best during the October 1997- September 1999 period for 3-month forecast horizon, GDP gap performs the best during the same period for 12-month forecast horizon. Although it lacks theoretical justifications, this approach is often used as one practical method for modellers to gauge information content of individual indicators over time.

### *IV.2 Multivariate Inflation Forecasts*

Table 6 summarises the forecast performance first by sector and then by model for multivariate models, which consists of both the combination forecast models (ridge, mean, median, and trimmed mean) and the factor model. In Panels A to D, we report model performance of economically homogenous groups as categorised in Table 2. Panel E presents model forecasts by simply combining all 66 indicators. Panel F exhibits model performance of a group of pre-selected indicators that outperform the benchmark at each of forecast horizon based on bivariate forecasts.

Consistent with bivariate forecasts, most models based on real sector activity indicators in Panel B perform better than those on other sectors at 3- and 6-month horizon, while models based on financial market indicators appear to perform better than those on real sector indicators and others over 12-month ahead forecast. Among all the sub-sectors, models based on labour market indicators in Panel B1 and on the pre- selected group of indicators in Panel F tend to perform better at all horizons considered. Multivariate models in Panels A (Money, deposit, and credit) and D (Prices) never appear to improve the benchmark for all forecast horizons considered.

Overall, four observations can be drawn from Table 6: First, although multivariate models do not always perform better than the AR model, especially at shorter forecast horizons, the better performing multivariate models always outperform the AR model and most of the bivariate models at a considerable margin. This implies that using multivariate models adds additional information and could improve the accuracy of inflation forecast. However, the bivariate model using job vacancy can outperform the benchmark much more than any multivariate models for all forecast horizons, that is, it gives us the smallest relative RMSE.

Second, we find that the multivariate models employing more indicators do not necessarily produce better forecast performance. In fact, using information from certain sub-sectors provides us with better forecast performance (*e.g.*, models in Panel B1 for the labour market sector and those in Panel F for a pre-selected group of indicators). This is in contrast with what is found in Stock and Watson (1999) in which an index that combines 168 indicators produces the best result.

Third, among all the multivariate methods utilised, factor models based on the principal component analysis produce forecasts with the least relative RMSEs at all three forecast horizons. Specifically, for h=3 and 12, the factor model using a pre-selected group of indicators that outperform the benchmark improves upon the AR forecasts by 6% and 15% in terms of the relative RMSEs. For h=6, the single factor model based on labour market indicators improves the AR model by 9%. However, when simply combining all indicators to form the first principal component, the factor model in general performs worse than the combination forecast models.

Fourth, our results indicate that the combination forecast models using mean, median, and trimmed mean appear to consistently outperform the benchmark AR model across all sectors except two: monetary sector group (Panel A) and various price indicators ( Panel D). Contrary to many other findings, our results appear to show that simple averages (mean or trimmed mean) appears to outperform the median forecasts consistently in general. The ridge regression combination forecasts outperform the AR model only at forecast horizon of 12 months when all indicators group (Panel E) and the group of pre-selected indicators (Panel F) are used.

### *IV.3 Sensitivity analysis*

The results presented in Table 6 are checked for robustness by a rolling regression with a fixed rolling window of 10 years. This is in contrast to the recursive estimation that holds the starting period of the regression sample unchanged. The rolling regression has the advantage of excluding observations from the distant past so that they will not influence the current observations and thereby can in principle accommodate the possibility of structural changes over the full sample period. However, the trade off is that it incorporates less information because of the foregone observations compared with the recursive estimation. It turns out that in most cases, for the same indicator or the same group of indicators, our recursive estimates produce smaller RMSEs on average than the rolling ones in all the models considered. On the basis of this comparison, our benchmark recursive estimation appears to be preferable.

## V. FORECASTING THE NON-RENTAL COMPONENT INFLATION

In view of the performance of various indicator-based models discussed in section IV, we select a number of preferred models based on their relative RMSEs over the out of sample forecast period and they are reported in Table 7. Based on the relative RMSEs alone, the bivariate model using job vacancy produces the lowest relative RMSEs and should be our most preferred model. However, as discussed in Stock and Watson (2003), bivariate forecasts often suffer from the problem of indicator instability in certain sample period and therefore solely relying on it may provide misleading forecasts. On the other hand, multivariate models appear to be able to accommodate this problem and should be considered as viable forecast models even if they record higher relative RMSEs than the best bivariate forecasts. Based on the relative RMSEs, we select two multivariate models, a factor model and a combination model with trimmed mean for both the labour market sector (Table 7: Panel B1) and a group of pre-selected indicators (Table 7: Panel F).

Table 8 reports the corresponding 3-, 6-, and 12-month non-rental component inflation forecasts based on the proposed models with forecasts made using data ending December 2005.[24] The bivariate model using the job vacancy indicator gives us a set of forecasts of 1.32%, 1.24% and 0.33%, respectively for the three forecast horizons. The projected increases in inflation over the first half of 2006 and the decline projected towards the year end imply quite a sharp change, reflecting a tapering down of the inflation pressure 12 months ahead based on the estimation from the job vacancy indicator alone. Despite the job vacancy indicator's impressive out-of-sample performance over 1998-2005, we need to treat the above results with caution, owing to possible forecast instability, a feature often characterising the bivariate forecasting models (Stock and Watson, 1999). Turing to the multivariate forecasts, our proposed models produce results broadly in the range of 0.32-0.77%, 0.49-0.81%, and 0.50-0.85% for 3-, 6-, and 12-month ahead inflation, respectively. In contrast to the bivariate forecasts, the range of inflation forecasts from our multivariate models (except an outlier produced by the factor model) appear to be more reasonable in view of our assessments of

[24] Note that these forecasts are annualized inflation forecasts for March-on-December, June-on-December, and December-on-December, respectively.

the prevailing economic conditions and forecasts projected from other models. Nevertheless, they still imply a tapering off of non-rental inflation in the second part of the year.

Table 9 reports the averaged year-on-year inflation forecasts as commonly reported. The columns labelled under 2006Q1, 2006H1, and 2006 correspond to forecasts made for respective horizons of 3, 6, and 12 months. The bivariate model using the job vacancy indicator provides us with a set of forecasts of 1.6%, 2.0% and 2.4%, respectively, for the three time periods under consideration. In comparison with the bivariate forecasts, the combination model of trimmed mean predicts more modest increases in inflation, ranging from 1.2%-1.3%, 1.3%-1.5%, and 1.6%-1.7%, respectively for the corresponding time horizons. While the forecast of the factor model (2.4%) is quite close to that based on the bivariate model at the 12-month forecast horizon, at horizons of 3 and 6 months, the factor model forecasts (1.1%-1.4% and 1.5%-1.8%, respectively) are quite similar to those of the combination model.

## VI. DISCUSSION AND CONCLUSION

This paper systematically evaluates out-of-sample forecastability of a set of 66 economic indicators in their relations to forecasting the non-rental component of Hong Kong's Inflation. We first use a bivariate model to examine these indicators individually and find that quite a few of them outperform the benchmark univariate AR model and some by a considerable margin. This suggests that these indicators do contain useful information and can be employed to enhance the accuracy of inflation forecasting. In particular, we find that the job vacancy indicator appears to consistently outperform the rest of indicators at all forecast horizons, followed by real GDP. To our surprise, some theoretically preferred and often adopted indicators in inflation forecasting such as unemployment rate and GDP gap do not perform particularly well when compared with the benchmark. In terms of indicators by sector, we find that real sector indicators, particularly the labour market ones, perform quite well at all forecast horizons, whereas indicators from the group of financial sector and asset prices perform well at longer forecast horizon, particularly that of 12 months.

We then employ multivariate models to investigate properties of combined forecasts and indicators. The results suggest that although multivariate models do not always perform better than the benchmark, when they do outperform, they usually improve upon both the benchmark and most of bivariate forecasts by a considerable margin. This implies that multivariate models can help improve inflation forecast. Different from the findings of other studies, we find that certain groups of our indicators (for example, labour market indicators and a pre-selected group of outperforming indicators) tend to perform better than simply combining all indicators. In terms of various types of multivariate models, we find that in our current data sample, factor models using certain groups of indicators appear to provide us with the best performance in terms of the relative RMSE. In addition, combination models using trimmed mean of individual inflation forecasts also perform well in certain circumstances.

Our preliminary results suggest that these indicator-based models are quite promising, although further research still needs to be carried out. In particular, more careful treatments of multivariate models such as the ridge regression methods and dynamic factor models should further enhance inflation forecastability. Moreover, better forecasts should be obtained by using other possible combinations of indicators as the current combinations are largely for illustrative purposes. Finally, we caution that these indicator models are still at their early stage of development. These models can be further refined and updated to improve our understanding of their performance.

## Table 1. Series Descriptions and Data Sample Periods

| Group | Variables | Description | Start | Frequency | SA | Transf.[1] |
|---|---|---|---|---|---|---|
| | | ***1. Money, deposit and credit*** | | | | |
| Money | *hkm1* | HK$ M1 | Oct-83 | M | SA | DLN |
| | *totm1* | Total M1 | Oct-83 | M | SA | DLN |
| | *hkm3a* | HK$ M3 (Adjusted to Include F.C. Swap Deposits) | Dec-84 | M | SA | DLN |
| | *hkm3* | HK$ M3 | Oct-83 | M | SA | DLN |
| | *totm3* | Total M3 | Oct-83 | M | SA | DLN |
| | *mbase** | Monetary Base Before Discount Window | Sep-98 | M | SA | DLN |
| | *mra93** | Foreign Currency Reserves Assets | Jun-93 | M | NSA | DLN |
| Deposit | *mhkdep* | HK$ deposits | Oct-83 | M | SA | DLN |
| | *usdep* | US$ deposits | Dec-84 | M | SA | DLN |
| | *othdep* | Non-US$ FC deposits | Dec-84 | M | SA | DLN |
| | *mtotdep* | Total deposits | Oct-83 | M | SA | DLN |
| Credit | *totloan* | Total Loans | Oct-83 | M | SA | DLN |
| | *domloan* | Domestic Loans | Oct-83 | M | SA | DLN |
| | *hkdloan* | HK$ loan | Oct-83 | M | SA | DLN |
| | | ***2. Real sector*** | | | | |
| Labour market | *umr* | Seasonally Adjusted Unemployment Rate (SA) | Oct-83 | M | SA | DLV, LV |
| | *emp81* | Employment (Incl Civil Servants) | Oct-83 | M | SA | DLN |
| | *unemp** | Unemployment | Sep-91 | M | SA | DLN |
| | *mlf91** | Labour Force | Sep-91 | M | SA | DLN |
| | *wagen* | Nominal wage index | Oct-83 | Q | SA | DLN, DDLN |
| | *vacancy* | Vacancy ( SA) | Oct-83 | Q | SA | DLN |
| | *payrolln* | Nominal payroll index | Oct-83 | Q | SA | DLN, DDLN |
| | *wkhr* | Working hours | Oct-83 | Q | SA | DLN |
| PMI | *pmi** | Purchasing Manager Index | Jul-98 | M | SA | LN |
| | *pmiin** | Purchasing Manager Index (Input) | Jul-98 | M | SA | LN |
| | *pmiout** | Purchasing Manager Index (output) | Jul-98 | M | SA | LN |
| Retail sales | *rsvsa* | Value index of Retail Sales(SA) | Oct-83 | M | SA | DLN |
| | *mrs* | Volume index of Retail Sales | Oct-83 | M | SA | DLN |
| Trade | *valtxtm* | Total Merchandise Trade (Im + Ex) | Oct-83 | M | SA | DLN |
| | *valtm* | Total Imports | Oct-83 | M | SA | DLN |
| | *valtx* | Total Exports | Oct-83 | M | SA | DLN |
| Output and its components | *ygap* | Output gap | Oct-83 | Q | NSA | DLV |
| | *gdpn* | GDP (at current market prices) | Oct-83 | Q | SA | DLN |
| | *gdpr* | GDP (at constant (2000) market prices) | Oct-83 | Q | SA | DLN |
| | *ip* | Industrial production index | Oct-83 | Q | SA | DLN |
| | *cin* | Inventory (at current market prices) | Oct-83 | Q | NSA | LV |
| | *cir* | Inventory (at constant (2000) market prices) | Oct-83 | Q | NSA | LV |
| | *gdfcfn* | Nominal Gross Domestic Fixed Capital Formation | Oct-83 | Q | SA | DLN |
| | *gdfcfr* | Real Gross Domestic Fixed Capital Formation | Oct-83 | Q | SA | DLN |
| | *prbcn* | Nominal Private Investment : Building and Construction | Oct-83 | Q | SA | DLN |
| | *prbcr* | Real Private Investment : Building and Construction | Oct-83 | Q | SA | DLN |
| | *pcen* | Nominal Private Consumption Expenditure | Oct-83 | Q | SA | DLN |
| | *pcer* | Real Private Consumption Expenditure | Oct-83 | Q | SA | DLN |
| Other variables | *ta* | Tourist arrival | Oct-83 | M | SA | DLN |

## Table 1. Series Descriptions and Data Sample Periods (Con't)

| Group | Variables | Description | Start | Frequency | SA | Transf.[1] |
|---|---|---|---|---|---|---|
| | | ***3. Financial sector and asset prices*** | | | | |
| Exchange | *hkdusd81* | HKD/USD | Oct-83 | M | NSA | DLN |
| Rates | *hkdrmb* | HKD/RMB | Oct-83 | M | NSA | DLN |
| | *neeri* | NEER Index | Oct-83 | M | NSA | DLN |
| | *Reeri* | REER Index (SA) | Oct-83 | M | SA | DLN |
| | *reericw* | REER Index - declining weight for Renminbi | Oct-83 | M | NSA | DLN |
| | *neeriexrmb* | NEER Index - excl RMB | Oct-83 | M | NSA | DLN |
| Interest rates | *Blra* | Best Lending Rate | Oct-83 | M | NSA | DLV, LV |
| | *hiboron* | Hong Kong Interbank Offer Rates : Overnight | Oct-83 | M | NSA | DLV, LV |
| | *hibor1m* | Hong Kong Interbank Offer Rates : 1-month | Oct-83 | M | NSA | DLV, LV |
| | *hibor3m* | Hong Kong Interbank Offer Rates: 3-month | Oct-83 | M | NSA | DLV, LV |
| | *hibor12m** | Hong Kong Interbank Offer Rates: 12-month | Jan-91 | M | NSA | DLV, LV |
| | *Libor3m* | Euro-dollar Deposit Rates: 3-month | Oct-83 | M | NSA | DLV, LV |
| | *Libor12m** | Euro-dollar Deposit Rates: 12-month | Feb-92 | M | NSA | DLV, LV |
| | *Tmdr1m* | HK$ Time Deposit Rate: 1-month | Oct-83 | M | NSA | DLV, LV |
| | *Tmdr3m* | HK$ Time Deposit Rate: 3-month | Oct-83 | M | NSA | DLV, LV |
| | *mfwdr** | Forward Rate (12M) | Jan-89 | M | NSA | DLV, LV |
| | *fundrate* | Effective funding rate | Jan-98 | M | NSA | DLV, LV |
| Asset market | *hsi* | Hang Seng Index | Oct-83 | M | NSA | DLN |
| | *hsipe* | Hang Seng Index P/E ratio | Oct-83 | M | NSA | DLN |
| | *propp93** | Private Domestic Property Price Index | Jan-93 | M | SA | DLN |
| | *cityppi** | Centa-City Property Price Index | Jan-94 | M | SA | DLN |
| | *rentres* | Rental Index of residential properties | Jan-90 | M | SA | DLN |
| | *rentretail* | Rental Index of retail properties | Jan-90 | M | SA | DLN |
| | *mspvol** | Agreement of Sale and Purchase | Aug-91 | M | SA | DLN |
| | *buyrentgap** | Buy-rental Gap | Jan-98 | M | NSA | DLV |
| | *rentalyld** | Rental Yield | Jan-98 | M | SA | DLV |
| | | ***4. Prices*** | | | | |
| Prices | *uvim* | Unit Value Index of Imports | Oct-83 | M | SA | DLN |
| | *uvix* | Unit Value Index of Exports | Oct-83 | M | SA | DLN |
| | *uvirm* | Unit Value Index of Retained Imports | Jan-89 | M | SA | DLN |
| | *ppi** | Producer Price Index | Jan-91 | Q | SA | DLN |
| Commodity | *wcomdp** | World Primary Commodity price | Feb-92 | M | NSA | DLN |
| Prices | *wcpexf* | World Primary Commodity price excluding fuel | Oct-83 | M | NSA | DLN |
| | *oilp* | World Oil Price | Oct-83 | M | NSA | DLN |
| External prices | *cncpi* | China Consumer Price Index | Oct-83 | M | SA | DLN |
| | | ***5. US indicators*** | | | | |
| | *uscpi* | US Consumer Prices | Oct-83 | M | SA | DLN |
| | *usffr* | US Federal Funds Rates | Oct-83 | M | NSA | DLV, LV |
| | *ustb3m* | 3-month US Treasury bill yield | Oct-83 | M | NSA | DLV, LV |
| | *ustn10y* | 10-year US Treasury yield | Oct-83 | M | NSA | DLV, LV |
| | *ussp10y* | Spread (10 year - 3 month US Treasury bill yield) | Oct-83 | M | NSA | DLV, LV |
| | *usumr* | Unemployment rate (% of civilian labour force, SA) | Oct-83 | M | SA | DLV, LV |
| | *usccapu* | Capacity utilization rate (%, SA) | Oct-83 | M | SA | LV |

Note:
* These indicators are not included in the current analysis due to a short period of coverage.
[1] Transformation performed for series $S_t$ is, $X_t = f(S_t)$. Specifically, LV: $X_t = S_t$, DLV: $Xt = S_t - S_{t-1}$, LN: $X_t = \ln S_t$, DLN: $X_t = \ln S_t - \ln S_{t-1}$, DDLN: $X_t = (\ln S_t - \ln S_{t-1}) - (\ln S_t - \ln S_{t-1})$.
Source: HKMA, C&SD, R&VD, CEIC, Datastream, Reuters, Centa Property, NTC research, and HK Tourism Board.

## Table 2. Time Series Property Tests

| | Description | Transf.[1,5] | Unit Root Test[2] ADF (p-value) | Unit Root Test[2] PP (p-value) | Granger Causality Test[3] (p-value) | Contemp. Correlation Coefficient |
|---|---|---|---|---|---|---|
| | ***1. Money, deposit and credit*** | | | | | |
| *hkm1* | HK$ M1 | DLN | 0 | 0 | 0.07 * | 0 |
| *totm1* | Total M1 | DLN | 0 | 0 | 0.04 ** | 0 |
| *hkm3a* | HK$ M3 (Adjusted to Include F.C. Swap Deposits) | DLN | 0 | 0 | 0.37 | -0.07 |
| *hkm3* | HK$ M3 | DLN | 0 | 0 | 0.22 | -0.05 |
| *totm3* | Total M3 | DLN | 0 | 0 | 0.27 | -0.06 |
| *mhkdep* | HK$ deposits | DLN | 0 | 0 | 0.28 | -0.09 |
| *usdep* | US$ deposits | DLN | 0 | 0 | 0.09 * | 0.05 |
| *othdep* | Non-US$ FC deposits | DLN | 0 | 0 | 0.09 * | 0.05 |
| *mtotdep* | Total deposits | DLN | 0 | 0 | 0.26 | -0.09 |
| *totloan* | Total Loans | DLN | 0.03 | 0 | 0.07 * | 0.01 |
| *domloan* | Domestic Loans | DLN | 0.03 | 0 | 0.07 * | -0.06 |
| *hkdloan* | HK$ loan | DLN | 0 | 0 | 0.10 | -0.07 |
| | ***2. Real sector*** | | | | | |
| *umr* | Seasonally Adjusted Unemployment Rate (SA) | LV | 0 | 0 | 0.01 ** | -0.17 |
| *emp81* | Employment (Incl Civil Servants) | DLN | 0 | 0 | 0.41 | -0.05 |
| *wagen* | Nominal wage index | DDLN | 0.84 | 0.04 | 0 ** | 0.09 |
| *vacancy* | Vacancy ( SA) | DLN | 0.04 | 0 | 0 ** | 0.04 |
| *payrolln* | Nominal payroll index | DDLN | 0.37 | 0 | 0.08 * | -0.02 |
| *wkhr* | Working hours | DLN | 0 | 0 | 0.42 | -0.10 |
| *rsvsa* | Value index of Retail Sales(SA) | DLN | 0 | 0 | 0.09 * | 0.23 |
| *mrs* | Volume index of Retail Sales | DLN | 0 | 0 | 0.01 ** | 0.29 |
| *valtxtm* | Total Merchandise Trade (Im + Ex) | DLN | 0 | 0 | 0 ** | -0.02 |
| *valtm* | Total Imports | DLN | 0 | 0 | 0 ** | -0.05 |
| *valtx* | Total Exports | DLN | 0 | 0 | 0 ** | 0.01 |
| *ygap* | Output gap | DLV | 0.02 | 0.01 | 0.06 * | 0.02 |
| *gdpn* | GDP (at current market prices) | DLN | 0 | 0 | 0.23 | 0 |
| *gdpr* | GDP (at constant (2000) market prices) | DLN | 0 | 0 | 0 ** | -0.03 |
| *ip* | Industrial production index | DLN | 0 | 0 | 0.22 | 0.14 |
| *cin* | Inventory (at current market prices) | LV | 0 | 0 | 0.28 | 0.10 |
| *cir* | Inventory (at constant (2000) market prices) | LV | 0.07 | 0 | 0.25 | 0.09 |
| *gdfcfn* | Nominal Gross Domestic Fixed Capital Formation | DLN | 0.02 | 0 | 0.12 | 0.01 |
| *gdfcfr* | Real Gross Domestic Fixed Capital Formation | DLN | 0 | 0 | 0.09 * | 0.01 |
| *prbcn* | Nominal Private Investment : Building and Construction | DLN | 0 | 0 | 0.94 | 0 |
| *prbcr* | Real Private Investment : Building and Construction | DLN | 0 | 0 | 0.67 | -0.05 |
| *pcen* | Nominal Private Consumption Expenditure | DLN | 0.10 | 0 | 0.13 | 0.08 |
| *pcer* | Real Private Consumption Expenditure | DLN | 0 | 0 | 0.05 * | 0.03 |
| *ta* | Tourist arrival | DLN | 0 | 0 | 0.21 | -0.03 |

## Table 2. Time Series Property Tests (con't)

| | Description | Transf.[1,5] | Unit Root Test[2] ADF (p-value) | Unit Root Test[2] PP (p-value) | Granger Causality Test[3] (p-value) | Contemp. Correlation Coefficient |
|---|---|---|---|---|---|---|
| | ***3. Financial sector and asset prices*** | | | | | |
| *hkdusd81* | HKD/USD | LV | 0 | 0 | 0.77 | 0.03 |
| *hkdrmb* | HKD/RMB | LV | 0 | 0 | 0.91 | 0.19 |
| *neeri* | NEER Index | DLN | 0 | 0 | 0.95 | -0.21 |
| *reeri* | REER Index (SA) | DLN | 0 | 0 | 0 ** | -0.05 |
| *reericw* | REER Index - declining weight for Renminbi | DLN | 0 | 0 | 0 ** | 0.01 |
| *neeriexrmb* | NEER Index - excl RMB | DLN | 0 | 0 | 0.18 | -0.07 |
| *blra* | Best Lending Rate | DLN | 0 | 0 | 0.69 | 0.01 |
| *hiboron* | Hong Kong Interbank Offer Rates : Overnight | LV | 0 | 0 | 0.97 | -0.03 |
| *hibor1m* | Hong Kong Interbank Offer Rates : 1-month | LV | 0 | 0 | 0.97 | 0.01 |
| *hibor3m* | Hong Kong Interbank Offer Rates: 3-month | LV | 0 | 0 | 0.93 | 0.02 |
| *libor3m* | Euro-dollar Deposit Rates: 3-month | DLN | 0 | 0 | 0.28 | 0.03 |
| *tmdr1m* | HK$ Time Deposit Rate: 1-month | DLN | 0 | 0 | 0.72 | 0.09 |
| *tmdr3m* | HK$ Time Deposit Rate: 3-month | DLN | 0 | 0 | 0.66 | 0.05 |
| *hsi* | Hang Seng Index | DLN | 0 | 0 | 0.68 | -0.05 |
| *hsipe* | Hang Seng Index P/E ratio | LV | 0 | 0 | 0.21 | 0.03 |
| *rentres* | Rental Index of residential properties | DLN | 0 | 0 | 0.46 | 0.05 |
| *rentretail* | Rental Index of retail properties | DLN | 0 | 0 | 0.27 | 0 |
| | ***4. Prices*** | | | | | |
| *uvim* | Unit Value Index of Imports | DLN | 0 | 0 | 0.33 | 0.16 |
| *uvix* | Unit Value Index of Exports | DLN | 0 | 0 | 0.35 | 0.12 |
| *uvirm* | Unit Value Index of Retained Imports | DLN | 0 | 0 | 0.77 | 0.03 |
| *wcpexf* | World Primary Commodity price excluding fuel | DLN | 0 | 0 | 0 ** | -0.03 |
| *oilp* | World Oil Price | DLN | 0 | 0 | 0.06 * | -0.04 |
| *cncpi* | China Consumer Price Index | DLN | 0 | 0 | 0.04 ** | 0.05 |
| | ***5. US indicators*** | | | | | |
| *uscpi* | US Consumer Prices | DLN | 0.03 | 0 | 0.12 | 0.09 |
| *usffr* | US Federal Funds Rates | DLN | 0 | 0 | 0.28 | 0.04 |
| *ustb3m* | 3-month US Treasury bill yield | DLN | 0 | 0 | 0.65 | 0.10 |
| *ustn10y* | 10-year US Treasury yield | DLN | 0 | 0 | 0.14 | -0.01 |
| *ussp10y* | Spread (10 year - 3 month US Treasury bill yield) | DLN | 0 | 0 | 0.41 | -0.10 |
| *usumr* | Unemployment rate (% of civilian labour force, SA) | DLN | 0 | 0 | 0.46 | 0.08 |
| *usccapu* | Capacity utilization rate (%, SA) | LV[4] | 0.28 | 0.26 | 0.55 | -0.01 |

Note:
[1] For variables adopted more than one type of transformation, reported results are for tests conducted based on the transformation assuming higher order of integration.
[2] To save space, we only report unit root test results for the transformed series.
[3] ** indicates p-value < 5%, * indicates p-value < 10%.
[4] We follow the literature and assume I(0) process for this variable.
[5] Transformation performed for series $S_t$ is, $X_t = f(S_t)$. Specifically, LV: $X_t = S_t$, DLV: $Xt = S_t - S_{t-1}$, LN: $X_t = \ln S_t$, DLN: $X_t = \ln S_t - \ln S_{t-1}$, DDLN: $X_t = (\ln S_t - \ln S_{t-1}) - (\ln S_t - \ln S_{t-1})$.
Source: Staff estimates.

## Table 3. Forecasting performance of various economic indicators, 1998 – 2005

| **Forecast Horizon** | | | h=3 | h=6 | h=12 |
|---|---|---|---|---|---|
| **Univariate** | | | | RMSE | |
| | | | 2.34 | 2.23 | 2.47 |
| **Bivariate** | | | | Rel. RMSE | |
| | ***1. Money, deposit and credit*** | | | | |
| *hkm1* | HK$ M1 | DLN | **0.98** | **0.97** | **0.96** |
| *totm1* | Total M1 | DLN | **0.99** | **0.96** | **0.95** |
| *hkm3a* | HK$ M3 (Adjusted to Include F.C. Swap Deposits) | DLN | 1.02 | 1.02 | 1.02 |
| *hkm3* | HK$ M3 | DLN | 1.02 | 1.01 | 1.03 |
| *totm3* | Total M3 | DLN | 1.04 | 1.03 | 1.14 |
| *mhkdep* | HK$ deposits | DLN | 1.01 | 1.01 | 1.03 |
| *usdep* | US$ deposits | DLN | 1.06 | 1.03 | 1.03 |
| *othdep* | Non-US$ FC deposits | DLN | 1.06 | 1.03 | 1.03 |
| *mtotdep* | Total deposits | DLN | 1.04 | 1.03 | 1.09 |
| *totloan* | Total Loans | DLN | 1.05 | 1.06 | 1.06 |
| *domloan* | Domestic Loans | DLN | 1.01 | 1.06 | 1.05 |
| *hkdloan* | HK$ loan | DLN | 1.01 | 1.04 | 1.05 |
| | ***2. Real sector*** | | | | |
| *umr* | Seasonally Adjusted Unemployment Rate (SA) | DLV | 1.07 | 1.05 | 1.02 |
| *emp81* | Employment (Incl Civil Servants) | DLN | 1.03 | 1.03 | 1.02 |
| *wagen* | Nominal wage index | DDLN | 1.01 | 1.00 | **1.00** |
| *vacancy* | Vacancy ( SA) | DLN | **0.90** * | **0.78** ** | **0.74** ** |
| *payrolln* | Nominal payroll index | DDLN | **1.00** | **0.99** | **0.99** |
| *wkhr* | Working hours | DLN | 1.02 | 1.00 | 1.01 |
| *rsvsa* | Value index of Retail Sales(SA) | DLN | 1.05 | 1.06 | 1.02 |
| *mrs* | Volume index of Retail Sales | DLN | **0.99** | **0.99** | **0.98** |
| *valtxtm* | Total Merchandise Trade (Im + Ex) | DLN | **0.99** | **0.98** | **0.97** |
| *valtm* | Total Imports | DLN | **0.99** | **0.98** | **0.98** |
| *valtx* | Total Exports | DLN | **0.99** | **0.98** | **0.97** |
| *ygap* | Output gap | DLV | **0.99** | **0.98** | **0.96** |
| *gdpn* | GDP (at current market prices) | DLN | 1.02 | 1.05 | 1.06 |
| *gdpr* | GDP (at constant (2000) market prices) | DLN | **0.98** | **0.90** * | **0.86** ** |
| *ip* | Industrial production index | DLN | **0.99** | **0.99** | 1.01 |
| *cin* | Inventory (at current market prices) | LV | 1.03 | 1.06 | 1.07 |
| *cir* | Inventory (at constant (2000) market prices) | LV | 1.02 | 1.06 | 1.08 |
| *gdfcfn* | Nominal Gross Domestic Fixed Capital Formation | DLN | 1.01 | 1.02 | 1.05 |
| *gdfcfr* | Real Gross Domestic Fixed Capital Formation | DLN | 1.03 | 1.01 | 1.03 |
| *prbcn* | Nominal Private Investment : Building and Construction | DLN | 1.06 | 1.07 | 1.06 |
| *prbcr* | Real Private Investment : Building and Construction | DLN | 1.03 | 1.03 | 1.03 |
| *pcen* | Nominal Private Consumption Expenditure | DLN | 1.08 | 1.06 | 1.10 |
| *pcer* | Real Private Consumption Expenditure | DLN | 1.02 | **0.94** * | **0.99** |
| *ta* | Tourist arrival | DLN | 1.29 | 1.19 | 1.25 |

## Table 3. Forecasting performance of various economic indicators, 1998 – 2005 (con't)

| **Forecast Horizon** | | | h=3 | h=6 | h=12 |
|---|---|---|---|---|---|
| **Univariate** | | | | RMSE | |
| | | | 2.34 | 2.23 | 2.47 |
| **Bivariate** | | | | Rel. RMSE | |
| | ***3. Financial sector and asset prices*** | | | | |
| *hkdusd81* | HKD/USD | LN | 1.02 | **0.99** | **0.95** * |
| *hkdrmb* | HKD/RMB | LN | 1.02 | 1.02 | 1.03 |
| *neeri* | NEER Index | DLN | 1.06 | 1.03 | 1.01 |
| *reeri* | REER Index (SA) | DLN | 1.10 | 1.03 | **0.95** * |
| *reericw* | REER Index - declining weight for Renminbi | DLN | 1.11 | 1.00 | **0.89** ** |
| *neeriexrmb* | NEER Index - excl RMB | DLN | 1.08 | 1.02 | **0.94** * |
| *blra* | Best Lending Rate | LV | **0.99** | **0.98** | **0.94** * |
| *hiboron* | Hong Kong Interbank Offer Rates : Overnight | LV | 1.02 | **0.99** | **0.98** |
| *hibor1m* | Hong Kong Interbank Offer Rates : 1-month | LV | 1.02 | **0.98** | **0.96** |
| *hibor3m* | Hong Kong Interbank Offer Rates: 3-month | LV | 1.03 | **0.97** | **0.96** |
| *libor3m* | Euro-dollar Deposit Rates: 3-month | DLV | **0.99** | **0.99** | 1.01 |
| *tmdr1m* | HK$ Time Deposit Rate: 1-month | LV | 1.02 | **0.98** | **0.94** |
| *tmdr3m* | HK$ Time Deposit Rate: 3-month | LV | 1.02 | **0.99** | **0.96** |
| *hsi* | Hang Seng Index | DLN | **0.99** | **0.97** | **0.97** |
| *hsipe* | Hang Seng Index P/E ratio | LN | **0.97** | **0.95** * | **0.98** |
| *rentres* | Rental Index of residential properties | DLN | 1.00 | 1.13 | **1.00** |
| *rentretail* | Rental Index of retail properties | DLN | 1.03 | 1.08 | 1.14 |
| | ***4. Prices*** | | | | |
| *uvim* | Unit Value Index of Imports | DLN | 1.05 | 1.04 | 1.03 |
| *uvix* | Unit Value Index of Exports | DLN | 1.05 | 1.07 | 1.08 |
| *uvirm* | Unit Value Index of Retained Imports | DLN | 1.19 | 1.21 | 1.19 |
| *wcpexf* | World Primary Commodity price excluding fuel | DLN | **0.98** | **0.98** | **0.97** |
| *oilp* | World Oil Price | DLN | **0.99** | **0.98** | 1.00 |
| *cncpi* | China Consumer Price Index | DLN | 1.03 | 1.03 | 1.04 |
| | ***5. US indicators*** | | | | |
| *uscpi* | US Consumer Prices | DLN | 1.02 | 1.02 | 1.06 |
| *usumr* | Unemployment rate (% of civilian labour force, SA) | DLN | 1.02 | 1.01 | 1.03 |
| *ustb3m* | 3-month US Treasury bill yield | DLV | 1.02 | **0.99** | 1.02 |
| *ustn10y* | 10-year US Treasury yield | DLV | 1.02 | **0.99** | 1.02 |
| *usffr* | US Federal Funds Rates | DLV | 1.02 | 1.00 | 1.02 |
| *ussp10y* | Spread (10 year - 3 month US Treasury bill yield) | DLV | 1.01 | 1.00 | 1.00 |
| *usccapu* | Capacity utilization rate (%, SA) | LV | 1.08 | 1.01 | **0.98** |

Note:
Bolded cell refers to the case when Rel. RMSE < 1.
** indicates Rel.RMSE < 0.90, and * indicates 0.90 ≤ Rel. RMSE ≤ 0.95.
Source: Staff estimates.

## Table 4. Sub-Forecas Sample Performance of indicators, h=6

| Projection Period | | Number of indicators that performed | | Root Mean Squared Error | |
|---|---|---|---|---|---|
| | | Better than Autoregression | Worse than Autoregression | Autoregression | Best Indicator |
| Oct-97 | Sep-99 | 45 | 21 | 1.54 | 0.97 (unemployment rate) |
| Oct-98 | Sep-00 | 33 | 33 | 1.63 | 1.15 (vacancy) |
| Oct-99 | Sep-01 | 24 | 42 | 0.82 | 0.66 (real effective exchange rate[1]) |
| Oct-00 | Sep-02 | 9 | 57 | 0.53 | 0.50 (Inventory at constant price) |
| Oct-01 | Sep-03 | 12 | 54 | 0.53 | 0.44 (vacancy) |
| Oct-02 | Sep-04 | 23 | 43 | 1.27 | 0.96 (vacancy) |
| Oct-03 | Sep-05 | 26 | 40 | 1.28 | 1.12 (vacancy) |

Note:
1 This index is calculated with a declining weight for Renminbi.
Source: Staff estimates.

## Table 5. Ranking the Inflation Indicators, 1998 - 2005, h=6

| **Indicator** | **Description** | **# of times the Indicator Outperforms Autoregression** | **Period and Indicators outperform the autoregression** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | **Oct-97 Sep-99** | **Oct-98 Sep-00** | **Oct-99 Sep-01** | **Oct-00 Sep-02** | **Oct-01 Sep-03** | **Oct-02 Sep-04** | **Oct-03 Sep-05** |
| *vacancy* | Vacancy ( SA) | 7 | * | * | * | * | * | * | * |
| *wagen* | Nominal wage index | 7 | * | * | * | * | * | * | * |
| *ustn10y* | 10-year US Treasury yield | 6 | * | * | | * | * | * | * |
| *hibor1m* | Hong Kong Interbank Offer Rates : 1-month | 5 | * | * | * | | | * | * |
| *hibor3m* | Hong Kong Interbank Offer Rates: 3-month | 5 | * | * | * | | | * | * |
| *tmdr1m* | HK$ Time Deposit Rate: 1-month | 5 | * | * | * | | | * | * |
| *hsi* | Hang Seng Index | 5 | * | * | * | | | * | * |
| *hsipe* | Hang Seng Index P/E ratio | 5 | * | * | * | | | * | * |
| *hkm1* | HK$ M1 | 4 | * | * | | | | * | * |
| *totm1* | Total M1 | 4 | * | * | | | | * | * |
| *payrolln* | Nominal payroll index | 4 | | * | * | | | * | * |
| *blra* | Best Lending Rate | 4 | * | * | | | | * | * |
| *hiboron* | Hong Kong Interbank Offer Rates : Overnight | 4 | | * | * | | | * | * |
| *tmdr3m* | HK$ Time Deposit Rate: 3-month | 4 | * | * | * | | | | * |
| *ustb3m* | 3-month US Treasury bill yield | 4 | | | * | * | * | | * |
| *ussp10y* | Spread (10 year - 3 month US Treasury bill yield) | 4 | * | * | | | | * | * |
| *mhkdep* | HK$ deposits | 3 | * | | | | | * | * |
| *usdep* | US$ deposits | 3 | | | * | | | * | * |
| *othdep* | Non-US$ FC deposits | 3 | | | * | | | * | * |
| *wkhr* | Working hours | 3 | | * | * | * | | | |
| *gdpr* | GDP (at constant (2000) market prices) | 3 | * | * | * | | | | |
| *cin* | Inventory (at current market prices) | 3 | | | * | * | * | | |
| *cir* | Inventory (at constant (2000) market prices) | 3 | | | * | * | * | | |
| *reeri* | REER Index (SA) | 3 | | | * | | | * | * |
| *reericw* | REER Index - declining weight for Renminbi | 3 | | | * | | | * | * |
| *libor3m* | Euro-dollar Deposit Rates: 3-month | 3 | * | * | * | | | | |
| *wcpexf* | World Primary Commodity price excluding fuel | 3 | * | * | | * | | | |

## Table 5. Ranking the Inflation Indicators, 1998 - 2005, h=6 (Con't)

| Indicator | Description | # of times the Indicator Outperforms Autoregression | Period and Indicators outperform the autoregression | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Oct-97 Sep-99 | Oct-98 Sep-00 | Oct-99 Sep-01 | Oct-00 Sep-02 | Oct-01 Sep-03 | Oct-02 Sep-04 | Oct-03 Sep-05 |
| *uscpi* | US Consumer Prices | 3 | * | * | * | | | | |
| *oilp* | World Oil Price | 3 | * | * | * | | | | |
| *usccapu* | Capacity utilization rate (%, SA) | 3 | * | * | | | | | * |
| *hkm3a* | HK$ M3 (Adjusted to Include F.C. Swap Deposits) | 2 | | | | | | * | * |
| *hkm3* | HK$ M3 | 2 | | | | | | * | * |
| *totloan* | Total Loans | 2 | * | | | | * | | |
| *domloan* | Domestic Loans | 2 | * | | | | * | | |
| *hkdloan* | HK$ loan | 2 | | | | * | * | | |
| *umr* | Seasonally Adjusted Unemployment Rate (SA) | 2 | * | * | | | | | |
| *mrs* | Volume index of Retail Sales | 2 | * | * | | | | | |
| *valtxtm* | Total Merchandise Trade (Im + Ex) | 2 | * | * | | | | | |
| *valtm* | Total Imports | 2 | * | * | | | | | |
| *valtx* | Total Exports | 2 | * | * | | | | | |
| *ygap* | Output gap | 2 | * | * | | | | | |
| *ip* | Industrial production index | 2 | * | * | | | | | |
| *gdfcfn* | Nominal Gross Domestic Fixed Capital Formation | 2 | * | * | | | | | |
| *gdfcfr* | Real Gross Domestic Fixed Capital Formation | 2 | * | * | | | | | |
| *prbcr* | Real Private Investment : Building and Construction | 2 | * | | | | * | | |
| *pcer* | Real Private Consumption Expenditure | 2 | * | * | | | | | |
| *hkdrmb* | HKD/RMB | 2 | * | | | | * | | |
| *neeri* | NEER Index | 2 | | | | | | * | * |
| *neeriexrml* | NEER Index - excl RMB | 2 | | | | | | * | * |
| *cncpi* | China Consumer Price Index | 2 | * | | | | * | | |
| *totm3* | Total M3 | 1 | * | | | | | | |
| *mtotdep* | Total deposits | 1 | * | | | | | | |
| *domloan* | Domestic Loans | 1 | | | | | * | | |
| *gdpn* | GDP (at current market prices) | 1 | * | | | | | | |
| *prbcn* | Nominal Private Investment : Building and Construction | 1 | * | | | | | | |
| *pcen* | Nominal Private Consumption Expenditure | 1 | * | | | | | | |
| *tmdr3m* | HK$ Time Deposit Rate: 3-month | 1 | | * | | | | | |
| *rentres* | Rental Index of residential properties | 1 | * | | | | | | |
| *ta* | Tourist arrival | 1 | | | * | | | | |
| *usumr* | Unemployment rate (% of civilian labour force, SA) | 1 | | * | | | | | |
| *usffr* | US Federal Funds Rates | 1 | * | | | | | | |
| *ustb3m* | 3-month US Treasury bill yield | 1 | | | | * | | | |
| *usffr* | US Federal Funds Rates | 1 | | | | * | | | |
| *usumr* | Unemployment rate (% of civilian labour force, SA) | 1 | | | | | * | | |

Source: Staff estimates.

# Table 6. Forecasting performance of multivariate models, 1998 – 2005

| **Forecast Horizon** | h=3 | h=6 | h=12 |
|---|---|---|---|
| **Univariate** | | RMSE | |
| | 2.34 | 2.23 | 2.47 |
| **Multivariate** | | Rel. RMSE | |
| Panel A. Money, Deposit and Credit | | | |
| Comb. ridge reg. | 1.73 | 1.53 | 1.15 |
| Comb. Mean | 1.01 | 1.01 | 1.01 |
| Comb. Median | 1.01 | 1.01 | 1.01 |
| Comb. Trimmed Mean | 1.01 | 1.01 | 1.02 |
| Factor Model | 1.03 | 1.05 | 1.06 |
| Panel A1. Money (Factor Model) | 1.02 | 1.03 | 1.01 |
| Panel A2. Deposit (Factor Model) | 1.06 | 1.04 | 1.06 |
| Panel A3. Credit (Factor Model) | 1.03 | 1.08 | 1.09 |
| Panel B. Real sector indicators | | | |
| Comb. ridge reg. | 1.62 | 1.31 | 1.00 |
| Comb. Mean | **0.99** | **0.96** | **0.97** |
| Comb. Median | **0.99** | **0.97** | **0.97** |
| Comb. Trimmed Mean | **0.98** | **0.96** * | **0.96** |
| Factor Model | 1.00 | 1.03 | 1.01 |
| Panel B1. Labour market indicators | | | |
| Comb. ridge reg. | 1.79 | 1.67 | 1.22 |
| Comb. Mean | **1.00** | **0.92** * | **0.99** |
| Comb. Median | **1.00** | **0.98** | **0.99** |
| Comb. Trimmed Mean | **0.95** | **0.92** * | **0.91** * |
| Factor Model | **0.95** * | **0.91** * | 1.00 |
| Panel B2. Other real activity indicators | | | |
| Comb. ridge reg. | 1.67 | 1.40 | 1.06 |
| Comb. Mean | **0.99** | **0.97** | **0.98** |
| Comb. Median | **0.99** | **0.98** | **0.98** |
| Comb. Trimmed Mean | **0.99** | **0.98** | **0.97** |
| Factor Model | 1.02 | 1.05 | 1.02 |
| Panel C. Financial market indicators | | | |
| Comb. ridge reg. | 1.70 | 1.45 | 1.04 |
| Comb. Mean | **1.00** | **0.96** | **0.93** * |
| Comb. Median | **1.00** | **0.96** | **0.93** * |
| Comb. Trimmed Mean | 1.00 | **0.96** | **0.92** * |
| Factor Model | 1.03 | **0.98** | **0.96** |
| Panel C1. Interest rates | | | |
| Comb. ridge reg. | 1.78 | 1.65 | 1.20 |
| Comb. Mean | 1.00 | **0.97** | **0.94** * |
| Comb. Median | 1.00 | **0.97** | **0.94** * |
| Comb. Trimmed Mean | 1.00 | **0.97** | **0.94** * |
| Factor Model | 1.02 | **0.98** | **0.96** |
| Panel C2. Exchange rates | | | |
| Comb. ridge reg. | 1.79 | 1.68 | 1.23 |
| Comb. Mean | 1.06 | **1.00** | **0.94** * |
| Comb. Median | 1.06 | 1.01 | **0.94** * |
| Comb. Trimmed Mean | 1.05 | **1.00** | **0.93** * |
| Factor Model | 1.12 | 1.03 | **0.94** * |
| Panel D. Prices | | | |
| Comb. ridge reg. | 1.78 | 1.66 | 1.26 |
| Comb. Mean | 1.01 | 1.03 | 1.04 |
| Comb. Median | 1.01 | 1.02 | 1.04 |
| Comb. Trimmed Mean | 1.02 | 1.03 | 1.04 |
| Factor Model | 1.10 | 1.18 | 1.22 |

## Table 6. Forecasting performance of multivariate models, 1998 – 2005 (con't)

| Forecast Horizon | h=3 | h=6 | h=12 |
|---|---|---|---|
| **Univariate** | | RMSE | |
| | 2.34 | 2.23 | 2.47 |
| **Multivariate** | | Rel. RMSE | |
| Panel E. All indicators | | | |
| Comb. ridge reg. | 1.39 | 1.09 | **0.94** * |
| Comb. Mean | **0.99** | **0.97** | **0.98** |
| Comb. Median | **0.99** | **0.98** | **0.98** |
| Comb. Trimmed Mean | **0.99** | **0.98** | **0.97** |
| Factor Model | **1.00** | 1.12 | **1.00** |
| Panel F. All indicators (outperform AR) | | | |
| Comb. ridge reg. | 1.68 | 1.27 | **0.93** * |
| Comb. Mean | **0.96** | **0.93** * | **0.93** * |
| Comb. Median | **0.96** | **0.95** | **0.93** * |
| Comb. Trimmed Mean | **0.95** | **0.94** * | **0.90** ** |
| Factor Model | **0.94** * | **0.93** * | **0.85** ** |

Note:
Bolded cell refers to the case when Rel. RMSE < 1.
** indicates Rel.RMSE < 0.90, and * indicates 0.90 ≤ Rel. RMSE ≤ 0.95.
Source: Staff estimates.

## Table 7. Proposed models and out-of-sample forecast performance (1998-2005)

| Forecast Horizon | h=3 | h=6 | h=12 |
|---|---|---|---|
| **Univariate** | | RMSE | |
| | 2.34 | 2.23 | 2.47 |
| | | Rel. RMSE | |
| **Bivariate** | | | |
| Vacancy | 0.90 | 0.78 | 0.74 |
| **Multivariate** | | | |
| Panel B1. Labour market indicators | | | |
| Comb. Trimmed Mean | 0.95 | 0.92 | 0.91 |
| Factor Model | 0.95 | 0.91 | - |
| Panel F. All indicators (outperform AR) | | | |
| Comb. Trimmed Mean | 0.95 | 0.94 | 0.90 |
| Factor Model | 0.94 | 0.93 | 0.85 |

Source: Staff estimates.

## Table 8. Model projections for h-month ahead non-rental component inflation (percentage change)

| Forecast Horizon | h=3 | h=6 | h=12 |
|---|---|---|---|
| **Univariate** | 0.30 | 0.40 | 0.48 |
| **Bivariate** | | | |
| Vacancy | 1.32 | 1.24 | 0.33 |
| **Multivariate** | | | |
| Panel B1. Labour market indicators | | | |
| Comb. Trimmed Mean | 0.77 | 0.71 | 0.60 |
| Factor Model | 0.49 | 0.81 | - |
| Panel F. All indicators (outperform AR) | | | |
| Comb. Trimmed Mean | 0.32 | 0.49 | 0.50 |
| Factor Model | -0.11 | 0.72 | 0.85 |

Note: Reported inflation figures are the h-month inflation for the non-rental component of HK CCPI at an annualised rate using data ending in December 2005.
Source: Staff estimates.

## Table 9. Model projections for averaged year-on-year non-rental component inflation (percentage change)

| Time Period<br>(Forecast Horizon) | 2006Q1<br>(3 months) | 2006H1<br>(6 months) | 2006<br>(12 months) |
|---|---|---|---|
| **Univariate** | 1.19 | 1.27 | 1.39 |
| **Bivariate** | | | |
| Vacancy | 1.63 | 2.02 | 2.36 |
| **Multivariate** | | | |
| Panel B1. Labour market indicators | | | |
| Comb. Trimmed Mean | 1.30 | 1.46 | 1.65 |
| Factor Model | 1.35 | 1.75 | - |
| Panel F. All indicators (outperform AR) | | | |
| Comb. Trimmed Mean | 1.19 | 1.33 | 1.58 |
| Factor Model | 1.14 | 1.54 | 2.40 |

Source: Staff estimates.

## REFERENCES

Altimari, Sergio Nicoletti (2001), "Does Money Lead Inflation in the Euro Area?", *Working Paper*, European Central Bank, No 63.

Atkeson, Andrew, and Lee E. Ohanian (2001), "Are Philips Curves Useful for Forecasting Inflation?", *Quarterly Review,* Federal Reserve Bank of Minneapolis, Vol. 25, No. 1, Winter, pp.2-11.

Banerjee, Anindya, Massimiliano Marcellino, and Igor Masten (2003), "Leading Indicators for Euro-area Inflation and GDP Growth", *Working paper,* I*nnocenzo Gasparini Institute for Economic Research,* No. 235.

Brave, Scott and Jonas D. M. Fisher (2004), "In Search of a Robust Inflation Forecast," *Economic Perspective*, Federal Reserve Bank of Chicago,,4Q, pp.12 – 31.

Bruneau, C, O. De Bandt, A. Flageollet, and E. Michaux (2003), "Forecasting Inflation Using Economic Indicators: the Case of France," *Working Paper*, Bank of France, No. 101.

Chan, Yeung Lewis, James H. Stock, and Mark W. Watson (1999), "A Dynamic Factor Model for Forecast Combination," *Spanish Economic Review*, 1, 91-122.

Cecchetti, Stephen G., Rita S. Chu, and Charles Steindel (2000), "The Unreliability of Inflation Indicators," *Current Issues in Economics and Finance,* April, Vol. 6, No.4.

Cristadoro, Riccardo, Mario Forni, Lucrezia Reichlin, and Giovanni Veronese (2005), "A Core Inflation Indicator for the Euro Area", *Journal of Money*, *Credit and Banking,* Vol. 37, No. 3, (June 2005).

Dion, Richard (1999), "Indicator Models of Core Inflation for Canada", July 1999, Bank of Canada, RM-99-013.

Fisher, Jonas D.M. (2000), "Forecasting Inflation with a Lot of Data", March 2000, Number 151, Essays on Issues, *Chicago Fed Letter*, Federal Reserve Bank of Chicago.

Fisher, Jonas D. M., Chin Liu, and Ruilin Zhou (2002), "When Can We Forecast Inflation?", *Economic Perspectives*, Federal Reserve Bank of Chicago,,First Quarter, pp.30-42.

Genberg, Hans and Laurent Pauwels (2002), "Inflation in Hong Kong, SAR – in Search of a Transmission Mechanism", *HEI Working Paper,* The Graduate Institute of International Studies, Geneva, No. 09/2002.

Gerlach, Stefan and Matthew S. Yiu (2004), "A Dynamic Factor Model for Current-Quarter Estimates of Economic Activity in Hong Kong", *Hong Kong Institute for Monetary Research Working Paper,* No. 16/2004.

Ha, Jiming, Cynthia Leung, and Chang Shu (2002), "A Small Macroeconomic Model of Hong Kong", *Research Memorandum* 07/2002, Hong Kong Monetary Authority.

Kitamura, Tomiyuki, and Ryoji Koike (2002), "The Effectiveness of Forecasting Methods Using Multiple Information Variables", *Institute for Monetary and Economic Studies (IMES) Discussion Paper Series,* Bank of Japan, 2002-E-20.

Kong, Janet and Cynthia Leung (2004), "Revised Small Forecasting Model for Hong Kong", *Research Memorandum* 13/2004, Hong Kong Monetary Authority.

Lansing, Kevin, J. (2002), "Can the Phillips Curve Help Forecast Inflation?" *Economic Letter*, Federal Reserve Bank of San Francisco, Number. 29, October 4: 1-3.

Leigh, Daniel and Marco Rossi (2002), "Leading Indicators of Growth and Inflation in Turkey", *IMF Working Paper*, WP/02/231.

Quinn, Terry and Andrew Mawdsley (1996), "Forecasting Irish Inflation: A Composite Leading Indicator", *Technical Paper,* Central Bank of Ireland, No. 4/RT/96.

Sekine, Toshitaka (2001), "Modelling and Forecasting Inflation in Japan," *IMF Working Paper*, WP/01/82.

Stock, James H. (2003), "The Econometric Analysis of Business Cycles", Department of Economics, Harvard University.

Stock, James H., and Mark W. Watson (1999), "Forecasting Inflation," *Journal of Monetary Economics,* Vol. 44, No.2.

________ (2001), "Forecasting Output and Inflation: the Role of Asset Prices," *NBER working paper* 8180.

________ (2002), "Forecasting Using Principal Components From a Large Number of Predictors", *Journal of the American Statistical Association*, Dec 2002, Vol. 97, No. 460, ABI/INFORM Global, pp.1167.

________ (2003), "Forecasting Output and Inflation: the Role of Asset Prices," *Journal of Economic Literature*, Vol. 41, No. 3, 788-829.