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# Forecasting Hong Kong Economy using Factor Augmented Vector Autoregression

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# **Forecasting Hong Kong Economy using Factor Augmented Vector Autoregression**

This work applies the FAVAR model to forecast GDP growth rate, unemployment rate and inflation rate of the Hong Kong economy. There is no factor model forecasting literature on the Hong Kong economy. The objective is to find out whether factor forecasting of using a large dataset can improve forecast performance of the Hong Kong economy. To avoid misspecification of the number of factors in the FAVAR, combination forecasts are constructed. It is found that forecasts from FAVAR model overall outperform simple VAR and AR models, especially when forecasting horizon increases. Generally, combination forecasts solve the misspecification problem.

## **1. Introduction**

The use of several common factors to summarize the information from a huge set of predictor variables has been the new frontier of the forecasting literature. It is well known that central banks actively monitor a large number of macroeconomic time series, and that monetary policy decisions would thus be based on the information contained in not only a few key aggregates but many economic variables. By employing all information from the available predictors, factor models can summarize many economic variables into few factors, and makes the forecasting more efficient.

Stock and Watson (1998, 1999 and 2002a) are the first to apply factor models in forecasting. These studies were about forecasting that involves very large data sets compared to the existing literature and they used pseudo out-of-sample forecast methods, either recursive or rolling forecasts, to evaluate and to compare forecasts results. Stock and Watson (1999) considered factor forecasts for U.S. inflation. The factors were estimated by Principal Component Analysis (PCA) from a panel of 147 monthly variables. They found that the forecasts based on a single real factor generally had lower pseudo out-of-sample forecast error than benchmark autoregressions and traditional Phillips-curve forecasts. Later, Stock and Watson (2002b) found substantial forecasting improvements for real variables using dynamic factors estimated by PCA from a panel of 215 U.S. monthly variables. Bernanke and Boivin (2003) confirmed the findings using real time data.

Following Stock and Watson (1999), factor models were applied to non-U.S. data for the purpose of forecasting.” Forni, Hallin, Lippi, and Reichlin (2003b) focused on

forecasting Euro-wide industrial production and inflation (HICP) using a monthly data set from February 1987 to March 2001 ( $T=170$ ) with 447 variables. They considered both PCA and weighted PCA forecasts, where the weighted principal components were constructed using the dynamic PCA weighting method introduced by Forni, Hallin, Lippi, and Reichlin (2003a). The PCA and weighted PCA forecasts performed similarly, and both exhibited improvements over the AR benchmark.

Brisson, Campbell, Galbraith (2003) examined the performance of factor based forecasts of Canadian GDP and investment growth using monthly and quarterly datasets from 1967 to 1998 ( $T=384$  for monthly dataset and  $T=128$  for quarterly dataset). They also experiment with Canadian only data and Canadian and US data. In the Canadian only dataset, there were 66 monthly variables and 62 quarterly variables, whereas in the Canadian and US dataset, there were 133 monthly variables and 119 quarterly variables. The static factors were estimated by PCA, and the static factors were lagged twice to compute forecasts with dynamic factor models. They find that the factor model forecasts improve substantially over AR models over the short horizon but not the longer horizon of 8-step ahead. Recently Cheung and Demers (2007) used quarterly data from 1973 Q1 to 2005 Q1 ( $T = 129$ ) with 324 Canadian variables and 112 U.S. variables and applied both static and dynamic factor models to generate forecasts on Canadian GDP growth and core inflation. They found that static factor models and dynamic factor models performed similarly in forecasting Canadian GDP and core inflation. And they found that one common factor suffices in longer samples while more factors are needed in shorter samples. In general, they found that factor model forecasts improve forecast accuracy up to 8-quarter ahead compared with AR models, IS curve model and Phillips-curve model.

Matheson (2006) compared factor model forecasts with the Reserve Bank of New Zealand's benchmark forecast using quarterly data from 1992 Q2 to 2004 Q3 ( $T=50$ ) with 384 variables. He found that at forecasting horizons longer than one year, forecasts of factor models outperformed the Reserve Bank's benchmark model. In addition, he found that utilizing all available variables than to limit predictors with good predictive performance in the past generated better out-of-sample forecasts.

The dynamic factor forecast described above is generally a linear function of dynamic factors and their lags and the lags of forecasting economic variables. A diverse approach was proposed by Bernanke, Boivin, and Elias (2005). They modeled the economic variables and the factors jointly as a variance autoregression (VAR), which they called it factor-augmented VAR (FAVAR). They applied the Stock and Watson

(1998, 2002) two-step principal component approach to monetary policy. The approach begins by using dynamic principal components to calculate the factors that summarize the most relevant information contained in a dataset. Then the estimated factors are stacked with the economic variable of interest and form a VAR. Although in their application they used the estimated model to evaluate monetary policy transmission mechanism by studying impulse responses, Stock and Watson (2004) commented that FAVAR could be used for forecasting by iterating the estimated FAVAR model  $h$ -steps ahead.

One application of FAVAR in the forecasting literature was conducted by Lagana and Mountford (2005) who applied U.K. data to FAVAR forecast. They used 150 U.K. variables from October 1992 to January 2001 ( $T=100$ ) and found that the FAVAR forecast improved with the number of factors.

There is no factor model forecasting literature on the Hong Kong economy. Our objective is to find out whether factor forecasting of using a large dataset can improve forecast performance of the Hong Kong economy. We thus apply the FAVAR model to forecast real GDP growth rate, unemployment rate and CPI inflation rate of the Hong Kong economy. We follow closely the Bernanke, Boivin, and Elias (2005) paper. 76 variables related to the Hong Kong economy are collected from June 1997 to September 2007 ( $T=125$ ). The dataset consists of 65 Hong Kong data, 7 Mainland data and 4 U.S. data. Like the BBE (2005) paper, we first estimate the factors using dynamic PCA and then estimate the factors and the forecasting variables jointly as a VAR. We compare  $h$ -step ahead out-of-sample forecasts of the FAVAR model against those of the benchmark VAR and the simple AR models. To avoid mis-specifying the number of factors in FAVAR models, we constructed combination forecasts from averages of individual forecasts of different numbers of factor.

We find that forecasts from FAVAR model in general outperform benchmark VAR and AR models, especially when forecasting horizon increases. However, forecasts based on FAVAR are sensitive to the number of factors enter the model. Combination forecasts of averaging different numbers of factors in general consistently perform better than benchmark models at almost all forecasting horizons, which can therefore solve the problem of mis-specification.

The paper proceeds as follows. Section 2 describes the FAVAR model. Section 3 provides a description of the dataset. Section 4 describes the out-of-sample forecasting exercise, and how to construct combination forecasts. Section 5 contains

the forecast results, and section 6 concludes.

## 2. FAVAR Model

Let  $F_t$  be a  $K \times 1$  vector of unobservable factors which can summarize most of the information contained in  $X$  which is an  $N \times 1$  stationary time series variables observed for  $t=1, \dots, T$ ;  $Y_t$  is an  $M \times 1$  observable macroeconomic variable and is a subset of  $X_t$ .

$F_t$  can be interpreted as factors that affect many economic variables. These factors can be extracted from observations on large information set in  $X_t$ . The number of informational time series,  $N$ , is large and may be larger than  $T$ , the number of time periods, and is assumed to be much larger than  $K+M$ . It is further assumed that the large information set is related to the unobserved factors,  $F_t$ , and the observable macroeconomic variables  $Y_t$ :

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + \varepsilon_t' \quad (1)$$

where  $\Lambda^f$  is an  $N \times K$  matrix of factor loadings,  $\Lambda^y$  is  $N \times M$ ,  $\varepsilon_t$  is an  $N \times 1$  vector of error terms that have mean zero and assumed to be weakly correlated. Equation (1) is the dynamic factor model developed by Stock and Watson (2002b). It implies that  $X_t$  is driven by both unobservable factors and observable macroeconomic variables, and therefore  $F_t$  and  $Y_t$  can be correlated. Since  $X_t$  can contain lagged values,  $F_t$  can be understood as containing arbitrary lags of fundamental factors. Advantage of the static representation of dynamic factor model of equation (1) is that it can be estimated by the principal component method (Stock and Watson, 2002b).

The joint dynamics of  $(F_t, Y_t)$  are given by

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = B(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \quad (2)$$

where  $B(L)$  is a conformable lag polynomial of finite order  $d$ ;  $e_t$  is an error term with mean zero and covariance matrix  $\Sigma$ .

If the terms in  $B(L)$  that relate  $Y_t$  to  $F_{t-1}$  are all zero, equation (2) is a standard VAR in  $Y_t$ , otherwise equation (2) is referred by BBE (2005) as a factor-augmented vector autoregression (FAVAR). If the true system is a FAVAR but instead equation (2) is

estimated as a standard VAR, that is, the factors are omitted, then the estimates in the standard VAR system will be biased.

Since  $F_t$  is a vector of unobservable factors, equation (2) can only be estimated after  $F_t$  is derived. In this paper, we apply the two-step estimation procedure in BBE (2005) to derive  $F_t$  first and then estimate equation (2).

It is reasonable to believe that information contained in  $X_t$  can be summarized into several categories. We call these categories as common components,  $C_t$ . In the first step of the two-step approach, we extract the first  $K+M$  principal components using all variables in  $X_t$ , and we get  $\widehat{C}_t$ . However, any of the linear combinations underlying  $\widehat{C}_t$  could involve the policy instrument, which is part of  $Y_t$ . Therefore it would be invalid to estimate a VAR of  $\widehat{C}_t$  and  $Y_t$ . We have to remove the dependence of  $\widehat{C}_t$  on the policy instrument. This requires identifying variables in  $X_t$  that is not related to the policy shock.

Since fast-moving variables in the dataset  $X_t$ , are highly sensitive to policy shocks, fast structural shocks and contemporaneous information, such as financial news and economic data release, BBE (2005) argue that there is high collinearity between fast-moving variables and policy shock. The logic implies that information contained in the fast-moving variables should be accounted for by the policy shock. On the contrary, slow-moving variables, for example real estate prices and sales, are assumed to be unaffected within the month by the policy shock, and these variables are marked with an asterisk in the Appendix.  $X_t$  is therefore split into slow-moving variables, the policy shock and fast-moving variables.

As slow-moving variables are not related to the policy shock contemporaneously, common components extracted from slow-moving variables,  $\widehat{F}_t^{slow}$ , are also not related to the policy shock contemporaneously.

Forming  $\widehat{C}_t$  such that

$$\widehat{C}_t = \beta^{slow} \widehat{F}_t^{slow} + \beta^Y Y_t + v_t \quad (3)$$

And then remove the dependence of  $\widehat{C}_t$  on the policy instrument to get the factors,  $\widehat{F}_t$ , in equation (2) as

$$\widehat{F}_t = \widehat{C}_t - \widehat{\beta}^Y Y_t \quad (4)$$

where  $\widehat{C}_t$  are principal components from  $X_t$  and  $\widehat{\beta}^Y$  comes from the result of equation (3).

Factors,  $\widehat{F}_t$ , obtained this way is part of the space covered by  $\widehat{C}_t$  that is not covered by  $Y_t$ , and therefore is now valid to enter VAR with  $Y_t$ . To identify unique factors against any rotation, restriction is imposed on factors by  $F'F/T=I^1$ .

In the second step, we estimate the FAVAR in equation (2) which consists of  $\widehat{F}_t$  and  $Y_t$ .

### 3. Data

76 variables related to the Hong Kong economy are collected, 65 of which are Hong Kong data, 7 are Mainland data and 4 are U.S. data. Due to limited Mainland data before the 1997 handover, the dataset is confined to the period from June 1997 to September 2007 ( $T=125$ ). All data are obtained from Bloomberg. The data are transformed such that all series become stationary. The transformation method follows the method used in Stock and Watson (2005). Variables and their transformations are listed in Appendix I.

### 4. Forecasting Method

Our objective is to forecast Hong Kong real GDP growth rate, unemployment rate and CPI inflation rate by FAVAR model and compare the forecasts with VAR and AR benchmark models.

Section 4.1 describes individual forecasts. Based on the FAVAR model there are four individual forecasting exercises. One is to forecast a three-variable vector of real GDP growth rate, unemployment rate and inflation rate all together. The other three forecasting exercises forecast the three variables one at a time.

Section 4.2 describes combination forecasts. For each individual forecast there are three combination forecasts. We constructed combination forecasts from averages of

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<sup>1</sup> We can impose restrictions on the factor loadings or the factors. Either approach provides the same common component and the same factor space.

FAVAR forecasts with different number of factors. The intention is try to avoid misspecification of  $K$  the FAVAR model.

Forecast results are compared to those of a benchmark VAR model and AR model.

#### 4.1 Individual Forecasting

There are four individual forecast exercises. All of them are based on the FAVAR model of equation (2).

##### FAVAR Forecast

Recall the FAVAR model

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = B(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \quad (2)$$

The  $h$ -step ahead forecast from this model is

$$Z_{t+h}^h = \Phi^h(L)Z_t + \Upsilon_{t+h}^h \quad (6)$$

where  $Z_t = \begin{bmatrix} F_t \\ Y_t \end{bmatrix}$ , is an  $(K + M) \times 1$  vector of  $K$  factors, and  $M$  forecasting variables;

$Z_{t+h}^h$  is the  $h$ -month ahead forecast of  $Z_t$ ;

$\Phi^h(L)$  is the iteratively estimated coefficients;

$\Upsilon_{t+h}^h$  is the  $h$ -month ahead forecast error term;

$K=1, \dots, 10$ .

The first forecast exercise is FAVAR forecast of a three-variable vector that contains real GDP growth rate, unemployment rate and inflation rate, and it is constructed in this order. In this case  $M=3$  in equation (6), and therefore we call this model FAVAR ( $M=3$ ). The other three individual forecast exercises forecast real GDP growth rate, unemployment rate and inflation rate one at a time using FAVAR. In this case  $M=1$  in equation (6), and we call this model FAVAR ( $M=1$ ).

Schwarz information criterion (SIC) determines the optimal lag length in each



forecast model. We limit the choice of lag length from one to thirteen.

The optimal number of factors has yet to be determined. Bai and Ng (2002) provided a criterion to determine the number of factors associated with the dataset,  $X_t$ . However, BBE (2005) pointed out that the criterion developed by Bai and Ng (2002) does not address the number of factors entering the FAVAR model in equation (2). BBE (2005) and Stock and Watson (2005) found that  $K=5$  and  $K=7$  are optimal in impulse response analyses when they applied U.S. data. Since there is no systematic way to determine the optimal number of factors in FAVAR all individual forecasts in this paper are carried out with  $K=1, \dots, 10$  respectively. The result should provide an insight into the choice of  $K$  when Hong Kong data is applied to FAVAR model.

### **Vector Autoregressive (VAR) Forecast**

The VAR model for vector  $Y_t$  is:

$$Y_t = B(L)Y_{t-1} + e_t \quad (7)$$

where  $Y_t$  is a an  $M \times 1$  vector of forecasting variables;

$B(L)$  is lag polynomial;

$e_t$  is an  $M \times 1$  vector of error terms.

The  $h$ -step ahead forecast from this model is:

$$Y_{t+h}^h = \Phi^h(L)Y_t + e_{t+h}^h \quad (8)$$

where  $Y_t$  is an  $M \times 1$  vector of forecasting variables;

$Y_{t+h}^h$  is the  $h$ -step ahead forecast of  $Y_t$ ;

$\Phi^h(L)$  is the iteratively estimated lag polynomials;

$e_{t+h}^h$  is the  $h$ -step ahead forecast error term.

The benchmark VAR forecast of equation (8) is applied to forecast a three-variable vector of real GPD growth rate, unemployment rate and inflation rate. The optimal lag length is chosen by SIC among one to thirteen.

### **Autoregressive (AR) Forecast**

The AR model is given by

$$y_t = \phi + \gamma(L)y_t + e_t \quad (9)$$

where  $y_t$  is the forecasting variable;

$\phi$  is a constant;

$\gamma(L)$  is the iteratively estimated lag polynomials, the lag order is chosen by SIC;

$e_t$  is the error term.

The  $h$ -step ahead forecast from this model is

$$y_{t+h}^h = \phi + \gamma^h(L)y_t + e_{t+h}^h \quad (10)$$

where  $y_{t+h}^h$  is the  $h$ -step ahead forecast of  $y_t$ .

$\gamma^h(L)$  is the iteratively estimated lag polynomials<sup>2</sup>;

$e_{t+h}^h$  is the  $h$ -month ahead forecast error term;

The benchmark AR forecast runs on real GDP growth rate, unemployment rate and inflation rate individually. The optimal lag length is chosen by SIC among one to thirteen.

### Forecast Performance Evaluation

Forecasts are made at 1-month to 12-month ahead horizons, i.e.  $h = 1, \dots, 12$ .

To obtain these forecasts, data is divided into an ‘in-sample’ set and an ‘out-of-sample’ set. The in-sample is set up for model estimation and lag length selection. The out-of-sample set is used for forecast performance evaluation.

Forecasts are based on rolling window approach. In a rolling window approach, the effective in-sample set is fixed at a particular number of data points. When the model is forecasted one-period forward the effective sample window rolls forward by one

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<sup>2</sup> This paper chooses iterated forecast specified in equation (10) against direct forecast. In a direct forecast,  $y_{t+h} = \gamma(L)y_t + e_{t+h}$ , forecasted value is not updated in the regressor for the next forecast horizon. Marcellino, Stock and Watson (2006) using a large U.S. economic data found that iterated forecast using AIC lag length selection performed better than direct forecasts, especially when forecast horizon increases. They argued that iterated forecast models with lag length selected based on information criterion are good estimate to the best linear predictor. And therefore the reduction in forecast variance arising from estimating the one-period ahead model outweighs the reduction in bias obtained from the direct multi-period model.

period. Rolling window approach is more robust to heterogeneity in data or when there is structural change in data which is not addressed by the model. In contrast to the rolling window approach, recursive approach expands the in-sample set and accumulates more information of the past when the model is forecasted forward. Recursive approach is preferred when the sample is considered homogenous over time. Since the FAVAR model and the benchmark VAR and AR models in this paper do not address structural change in the sample, the rolling approach is preferred.

The rolling window is set to contain 100 observation periods so that only the most update 100 periods of the in-sample are used for factor extraction, coefficient estimation and lag length selection. Factors, coefficients and lag length are re-estimated for each period when the sample window rolls forward.

Put it explicitly, the first out-of-sample forecast was made from 2005:09. Factors, coefficients and lag length of the models were estimated from sample of 1997:06 through 2005:09, which consists of 100 observations, to forecast  $y^h_{2005:09+h}$ . All factors, coefficients and lag length are then re-estimated for the next period in the out-of-sample set so that the data from 1997:07 through 2005:10 are used for forecast  $y^h_{2005:10+h}$ , and so on.

Root mean square error (RMSE) at each forecast horizon  $h$  is constructed from forecast errors to measure performance of forecasting models.

$$\text{RMSE}_h = \sqrt{\frac{1}{J-h} \sum_{t=T-J}^{T-h} (e_{t+h}^h)^2} \quad (7)$$

where  $J$  is the out-of-sample size from 2005:10 to 2007:09;

$h$  is the forecasting horizon;

$e_{t+h}^h$  is the forecast error at period  $t$  at forecast horizon  $h$ .

## 4.2 Combination forecast

In the second part of the forecasting exercise, we try to compute combination forecasts using simple averaging of individual forecast results in Section 4.1. Literatures dating back to Newbold and Granger (1974) show that combining forecasts often outperform individual forecasts, which could suffer from model misspecification.

In FAVAR, misspecification could arise if  $K$  in the model is different from that of the

underlying model. Since the optimal number of factors changes with forecasting horizon as well as the variable of interest, a unique  $K$  that can generate forecasts with minimum RMSE cannot be guaranteed at all  $h$ . Averaging FAVAR forecasts with different  $K$  could yield more consistent outcome than individual forecasts.

Although the choices of  $K$  are one to ten, results from individual forecasts in Section 5 indicate that few  $K$  could be candidates of the optimal number of factors to enter the model. Since there are too few individual forecasts to be averaged as a single forecast, it is impossible to run OLS estimation to get the weights of average or to calculate trim-mean and median to serve as the combination forecast. We therefore rely on forecast results in Section 5 to suggest candidates of the optimal number of factors. Average of these individual forecasts is the combination forecast. Results in Section 5 shows that individual forecasts of two-factor and three-factor FAVAR models perform better than their benchmark models when the forecasting variables are real GDP growth rate and unemployment rate. On the other hand, forecasts of inflation from FAVAR with three to ten factors outperform the benchmark models. We therefore propose three combination forecasts that are simple averages of FAVAR forecast with  $K=1,\dots,2$ ;  $K=1,\dots,3$  and  $K=1,\dots,10$  respectively.

## 5. Forecasting Results

We find that forecast performance from FAVAR model relative to benchmark models is sensitive to  $K$  in FAVAR. When the variables of interest are real GDP growth rate and unemployment rate, forecasts from FAVAR with two to three factors outperform benchmark VAR and AR models. On the other hand, when the variable of interest is CPI inflation then FAVAR models with three to ten factors produce better forecasts than benchmark models, among them FAVAR with three factors produces the most accurate forecast in terms of RMSEs. Our results therefore are mixed compare with those of Lagana and Mountford (2005) that find FAVAR with more factors produce better forecasts of UK short-term interest rate than benchmark forecasts. The difference in findings could be a result of different variables of interest as well as different datasets.

Results from combination forecasts show that averages of FAVAR forecasts with different  $K$  consistently perform better than benchmark models at almost all horizons. However, there is one drawback. Since individual forecast results show that the optimal number of factors to enter FAVAR varies with the variable of interests, the

range of  $K$  still has to be chosen correctly in combination forecast. Apart from this, combining forecasts can in fact avoid poor forecasts result from misspecification of  $K$  in FAVAR.

FAVAR models that can beat the benchmarks have smaller ratios of RMSE compare with benchmark models when forecasting horizon increases. Although it is true that FAVAR models sometimes perform worse than the benchmarks at  $h=1,2$ , it is clear that performance of FAVAR forecast is better than benchmark models at longer horizon.

Table 1.1 shows RMSEs of real GDP growth forecasts from FAVAR ( $M=3$ ) model. In this model  $Y_t$  is a vector that contains real GDP, unemployment rate and CPI inflation. Table 1.2 shows RMSEs of real GDP growth forecast from FAVAR ( $M=1$ ) model. In this model  $Y_t$  contains only real GDP growth rate. Table 2 and Table 3 show RMSEs of CPI inflation rate and unemployment rate respectively. Results from FAVAR ( $M=3$ ) and FAVAR ( $M=1$ ) are shown in separate tables.

The tables also show results from combination forecasts, and compares them with benchmark VAR and AR models.

RMSE ratio of less than 1 means forecast from the respective FAVAR model performs better than those of benchmark model. All the ratios less than 1 are displayed in orange.

### **5.1 Forecast results of real GDP growth rate**

Table 1.1 shows that individual forecast of FAVAR ( $M=3$ ) with  $K=2$  outperform VAR and AR benchmarks at  $h=2, \dots, 12$ , and at  $h=2, \dots, 10$  respectively. For forecasts at horizons that perform worse than AR, RMSEs of the FAVAR model and those of benchmarks are actually very close. Combination forecasts from averaging FAVAR with  $K=1, \dots, 3$  and  $K=1, 2$  respectively show similar results, even they still cannot beat VAR at the first horizon the differences are negligible.

Table 1.2 shows that in general individual forecasts of real GDP from FAVAR ( $M=1$ ) model produce lower RMSEs than FAVAR ( $M=3$ ). Forecasts of FAVAR ( $M=1$ ) with  $K=2$  can beat AR with horizons  $h=2, \dots, 12$ . Combination forecasts of averaging  $K=1, \dots, 2$  outperform AR model at almost all horizons.

## 5.2 Forecast results of CPI inflation

Table 2.1 shows that FAVAR ( $M=3$ ) forecasts of CPI inflation perform very well. With  $K=3$  to  $K=10$ , the forecasts beat the VAR benchmark at almost all horizons. The model with  $K=3$  beat AR models at all horizons. All the combination forecasts beat VAR forecasts at all horizons. Combination forecasts averaging forecasts of FAVAR with  $K=1,2$  outperform AR model except at  $h=4,5,6$ , however, the differences of RMSEs are very small.

FAVAR ( $M=1$ ) forecasts of CPI inflation produce lower RMSEs than FAVAR ( $M=3$ ) in general as shown in Table 2.2. For  $K=3$  to  $K=10$ , FAVAR ( $M=1$ ) forecasts outperform AR forecasts except in 6 incidents when  $h=1,2$ . Combination forecasts of averaging forecasts of FAVAR with  $K=1,\dots,10$  perform better than AR forecasts at all horizons.

## 5.3 Forecast results of unemployment rate

Table 3.1 shows that individual forecasts of unemployment rate from FAVAR ( $M=3$ ) with  $K=2$  surpass the performance of VAR. However, combination forecasts from this model only performs better than VAR at longer horizons of  $h=9,\dots,12$ . All combination forecasts perform better than AR forecasts except only when the forecast combined averages of FAVAR with  $K=1,\dots,10$  at horizon  $h=2$ .

From Table 3.2, we can see that forecasts from FAVAR ( $M=1$ ) in general perform worse than FAVAR ( $M=3$ ) in terms of RMSEs. This result is opposite to those found in forecasts of real GDP growth rate and inflation rate.

For  $K=1$  to  $K=4$ , individual forecasts from FAVAR ( $M=1$ ) are better than those from AR model. All combination forecasts outperform AR forecasts at all horizons, except in 2 incidents when forecasts are combined averages of FAVAR with  $K=1,\dots,10$  at  $h=1,2$ .

## 6. Conclusion

This paper applies factor-augmented VAR (FAVAR) model to forecast real GDP growth rate, CPI inflation and unemployment rate of the Hong Kong economy. No existing literature has applied factor model to the Hong Kong economy. The

application of FAVAR allows the use of a large dataset, information from the dataset is extracted into factors that enter VAR jointly with the forecasting variables. Results show that factors from the dataset can improve forecast performance on benchmark VAR and AR models especially for long forecast horizons. Out-of-sample forecasts show that the model is especially good at CPI inflation forecast. It is also found that the number of factors enters the model affects forecast performance. Using combination forecasts that are averages of FAVAR with different numbers of factor as a single forecast can avoid misspecification arises from the choice of number of factors in FAVAR. Results show that combination forecasts consistently perform better than benchmark models at almost all forecasting horizons.

The following tables show RMSEs of the out-of-sample forecasts of real GDP growth rate, CPI inflation rate and unemployment rate from FAVAR and FAAR respectively. They are based on 100-month rolling window forecasts. The out-of-sample period is October 2005-September 2007 (24 months). Ratios of RMSE less than 1 are in orange, they represent smaller RMSEs compare to the benchmark models. Note:  $h$  is forecasting horizon.

**Table 1.1 RMSE of Out-of-sample Forecast of Real GDP growth from FAVAR (M=3) model:**

FAVAR (M=3) rgdp lags=1 K=0~10 h=1~12		K	VAR	1	2	3	4	5	6	7	8	9	10	avg K=1~10	avg K=1~3	avg K=1~2	AR
h	1	0.2219	0.2204	0.2260	0.2296	0.2265	0.2962	0.3360	0.3101	0.2877	0.3047	0.2928	0.2474	0.2242	0.2220	0.2226	
	2	0.2838	0.2792	0.2763	0.2823	0.2761	0.3267	0.3926	0.3690	0.3468	0.3625	0.3506	0.3019	0.2782	0.2767	0.2775	
	3	0.2832	0.2775	0.2649	0.2830	0.2782	0.3249	0.4292	0.4174	0.3932	0.4196	0.4045	0.3229	0.2740	0.2700	0.2720	
	4	0.2815	0.2722	0.2417	0.2731	0.2804	0.3336	0.4760	0.4791	0.4528	0.4868	0.4694	0.3499	0.2612	0.2558	0.2721	
	5	0.2847	0.2735	0.2260	0.2717	0.3007	0.4047	0.5438	0.5601	0.5332	0.5788	0.5597	0.3986	0.2561	0.2488	0.2745	
	6	0.3178	0.3006	0.2397	0.2969	0.3492	0.4947	0.6344	0.6635	0.6353	0.6909	0.6710	0.4700	0.2783	0.2694	0.2993	
	7	0.3351	0.3117	0.2448	0.3098	0.3726	0.5492	0.7000	0.7446	0.7117	0.7867	0.7651	0.5179	0.2878	0.2773	0.2896	
	8	0.3594	0.3276	0.2505	0.3283	0.4004	0.6058	0.7797	0.8456	0.8068	0.9080	0.8850	0.5783	0.3011	0.2879	0.2795	
	9	0.4127	0.3798	0.2931	0.3784	0.4542	0.6898	0.8857	0.9717	0.9269	1.0613	1.0365	0.6642	0.3492	0.3350	0.3055	
	10	0.4884	0.4523	0.3520	0.4501	0.5369	0.8117	1.0327	1.1381	1.0905	1.2549	1.2272	0.7830	0.4167	0.4006	0.3584	
	11	0.5716	0.5319	0.4174	0.5279	0.6285	0.9319	1.2028	1.3284	1.2777	1.4738	1.4402	0.9156	0.4909	0.4730	0.4137	
	12	0.6388	0.5922	0.4564	0.5915	0.7159	1.0605	1.3945	1.5410	1.4838	1.7131	1.6738	1.0557	0.5456	0.5230	0.4374	
Ratio of RMSE VS VAR																	
h	1	1.0000	0.9932	1.0187	1.0346	1.0209	1.3347	1.5141	1.3977	1.2966	1.3732	1.3196	1.1151	1.0102	1.0004	1.0033	
	2	1.0000	0.9838	0.9735	0.9948	0.9728	1.1509	1.3833	1.2999	1.2219	1.2771	1.2351	1.0637	0.9803	0.9747	0.9777	
	3	1.0000	0.9799	0.9356	0.9994	0.9825	1.1475	1.3886	1.4741	1.3886	1.4816	1.4286	1.1402	0.9676	0.9534	0.9606	
	4	1.0000	0.9668	0.8587	0.9700	0.9959	1.1848	1.6907	1.7017	1.6084	1.7291	1.6674	1.2430	0.9279	0.9085	0.9664	
	5	1.0000	0.9608	0.7940	0.9544	1.0561	1.4217	1.9100	1.9674	1.8731	2.0330	1.9660	1.4002	0.8997	0.8741	0.9643	
	6	1.0000	0.9458	0.7544	0.9344	1.0990	1.5568	1.9963	2.0878	1.9993	2.1741	2.1114	1.4791	0.8757	0.8479	0.9418	
	7	1.0000	0.9302	0.7306	0.9245	1.1117	1.6388	2.0888	2.2221	2.1238	2.3476	2.2832	1.5454	0.8589	0.8274	0.8641	
	8	1.0000	0.9116	0.6969	0.9136	1.1141	1.6857	2.1698	2.3530	2.2451	2.5267	2.4627	1.6092	0.8379	0.8010	0.7778	
	9	1.0000	0.9204	0.7101	0.9170	1.1007	1.6715	2.1463	2.3547	2.2461	2.5719	2.5118	1.6094	0.8461	0.8118	0.7404	
	10	1.0000	0.9261	0.7208	0.9216	1.0994	1.6621	2.1147	2.3305	2.2330	2.5697	2.5130	1.6034	0.8534	0.8202	0.7340	
	11	1.0000	0.9306	0.7302	0.9235	1.0996	1.6305	2.1044	2.3241	2.2354	2.5785	2.5197	1.6020	0.8588	0.8275	0.7238	
	12	1.0000	0.9271	0.7145	0.9260	1.1207	1.6602	2.1831	2.4124	2.3229	2.6818	2.6203	1.6527	0.8541	0.8187	0.6847	
Ratio of RMSE VS AR																	
h	1	0.9967	0.9900	1.0154	1.0312	1.0175	1.3303	1.5091	1.3931	1.2924	1.3687	1.3153	1.1114	1.0069	0.9971	1.0000	
	2	1.0228	1.0062	0.9956	1.0174	0.9949	1.1771	1.4148	1.3295	1.2498	1.3062	1.2632	1.0879	1.0026	0.9969	1.0000	
	3	1.0410	1.0201	0.9740	1.0404	1.0228	1.1946	1.5778	1.5345	1.4455	1.5424	1.4872	1.1870	1.0073	0.9925	1.0000	
	4	1.0348	1.0004	0.8885	1.0037	1.0305	1.2260	1.7495	1.7609	1.6644	1.7892	1.7253	1.2862	0.9601	0.9401	1.0000	
	5	1.0370	0.9963	0.8233	0.9897	1.0952	1.4743	1.9807	2.0402	1.9424	2.1083	2.0387	1.4520	0.9330	0.9064	1.0000	
	6	1.0617	1.0042	0.8010	0.9920	1.1668	1.6529	2.1196	2.2167	2.1228	2.3083	2.2418	1.5704	0.9298	0.9002	1.0000	
	7	1.1572	1.0765	0.8455	1.0699	1.2865	1.8965	2.4172	2.5714	2.4577	2.7168	2.6422	1.7883	0.9939	0.9575	1.0000	
	8	1.2857	1.1720	0.8961	1.1746	1.4325	2.1673	2.7897	3.0253	2.8866	3.2487	3.1664	2.0691	1.0772	1.0299	1.0000	
	9	1.3506	1.2432	0.9592	1.2385	1.4867	2.2576	2.8989	3.1804	3.0337	3.4736	3.3925	2.1738	1.1428	1.0964	1.0000	
	10	1.3624	1.2618	0.9821	1.2556	1.4979	2.2645	2.8811	3.1751	3.0424	3.5010	3.4237	2.1845	1.1626	1.1175	1.0000	
	11	1.3817	1.2858	1.0089	1.2760	1.5193	2.2528	2.9076	3.2112	3.0886	3.5627	3.4814	2.2134	1.1866	1.1433	1.0000	
	12	1.4605	1.3540	1.0436	1.3525	1.6369	2.4248	3.1884	3.5234	3.3926	3.9169	3.8271	2.4138	1.2474	1.1957	1.0000	



**Table 1.2 RMSE of Out-of-sample Forecast of Real GDP growth from FAVAR (M=1) model:**

FAVAR (M=1) rgdp lags=1 K=0~10 h=1~12		K	AR	1	2	3	4	5	6	7	8	9	10	avg K=1~10 lags=1	avg K=1~3 lags=1	avg K=1~2 lags=13
h	1	0.2226	0.2213	0.2268	0.2222	0.2259	0.2348	0.2709	0.2540	0.2372	0.2226	0.2459	0.2235	0.2199	0.2006	
	2	0.2775	0.2783	0.2759	0.2775	0.2800	0.2737	0.3269	0.3111	0.2925	0.2788	0.2941	0.2769	0.2741	0.2703	
	3	0.2720	0.2734	0.2607	0.2780	0.2777	0.2600	0.3463	0.3451	0.3223	0.3125	0.3186	0.2846	0.2671	0.2740	
	4	0.2721	0.2733	0.2382	0.2720	0.2699	0.2539	0.3710	0.3896	0.3621	0.3567	0.3602	0.2981	0.2571	0.2595	
	5	0.2745	0.2743	0.2188	0.2706	0.2672	0.2988	0.4155	0.4537	0.4230	0.4233	0.4332	0.3296	0.2500	0.2353	
	6	0.2993	0.2983	0.2327	0.2956	0.2929	0.3678	0.4845	0.5402	0.5064	0.5109	0.5291	0.3858	0.2705	0.2455	
	7	0.2896	0.2886	0.2289	0.3095	0.3065	0.3988	0.5266	0.6045	0.5630	0.5757	0.5970	0.4150	0.2693	0.2370	
	8	0.2795	0.2790	0.2229	0.3294	0.3237	0.4239	0.5771	0.6855	0.6342	0.6576	0.6833	0.4520	0.2698	0.2370	
	9	0.3055	0.3080	0.2453	0.3820	0.3708	0.4791	0.6527	0.7890	0.7257	0.7626	0.7925	0.5132	0.3044	0.2027	
	10	0.3584	0.3636	0.2865	0.4550	0.4369	0.5665	0.7630	0.9287	0.8544	0.9067	0.9452	0.6056	0.3610	0.1960	
	11	0.4137	0.4219	0.3320	0.5352	0.5108	0.6555	0.8912	1.0891	1.0012	1.0717	1.1149	0.7087	0.4215	0.2372	
	12	0.4374	0.4477	0.3373	0.6001	0.5682	0.7385	1.0283	1.2625	1.1564	1.2524	1.3019	0.8103	0.4541	0.2992	
Ratio of RMSE VS AR																
h	1	1.0000	0.9943	1.0186	0.9980	1.0147	1.0547	1.2169	1.1411	1.0656	0.9999	1.1044	1.0041	0.9876	0.9013	
	2	1.0000	1.0028	0.9942	1.0000	1.0089	0.9861	1.1781	1.1211	1.0541	1.0045	1.0597	0.9978	0.9876	0.9738	
	3	1.0000	1.0051	0.9584	1.0222	1.0210	0.9560	1.2731	1.2688	1.1847	1.1490	1.1711	1.0464	0.9819	1.0074	
	4	1.0000	1.0044	0.8756	0.9996	0.9922	0.9333	1.3638	1.4320	1.3308	1.3112	1.3240	1.0957	0.9448	0.9537	
	5	1.0000	0.9993	0.7968	0.9856	0.9733	1.0884	1.5136	1.6526	1.5409	1.5419	1.5781	1.2005	0.9108	0.8572	
	6	1.0000	0.9966	0.7774	0.9877	0.9784	1.2289	1.6186	1.8050	1.6920	1.7069	1.7678	1.2888	0.9039	0.8204	
	7	1.0000	0.9964	0.7903	1.0686	1.0583	1.3773	1.8186	2.0874	1.9442	1.9880	2.0616	1.4330	0.9301	0.8183	
	8	1.0000	0.9984	0.7975	1.1787	1.1580	1.5165	2.0646	2.4526	2.2689	2.3529	2.4446	1.6172	0.9653	0.8478	
	9	1.0000	1.0082	0.8028	1.2502	1.2137	1.5680	2.1361	2.5824	2.3752	2.4959	2.5938	1.6796	0.9964	0.6633	
	10	1.0000	1.0144	0.7992	1.2694	1.2190	1.5805	2.1288	2.5909	2.3837	2.5295	2.6370	1.6894	1.0070	0.5469	
	11	1.0000	1.0198	0.8026	1.2936	1.2348	1.5847	2.1543	2.6327	2.4202	2.5906	2.6951	1.7132	1.0190	0.5734	
	12	1.0000	1.0236	0.7711	1.3720	1.2991	1.6885	2.3512	2.8866	2.6440	2.8635	2.9767	1.8527	1.0382	0.6840	

**Table 2.1 RMSE of Out-of-sample Forecast of CPI from FAVAR (M=3) model:**

FAVAR (M=3) cpi lags=1 K=0~10 h=1~12		K	VAR	1	2	3	4	5	6	7	8	9	10	avg K=1~10	avg K=1~3	avg K=1~2 lags=13	AR
h	1	0.3359	0.3373	0.3353	0.3050	0.3051	0.3315	0.3133	0.3309	0.3130	0.3120	0.3071	0.3140	0.3175	0.2556	0.3077	
	2	0.3569	0.3586	0.3562	0.3225	0.3249	0.3704	0.3475	0.3660	0.3388	0.3377	0.3420	0.3409	0.3369	0.3188	0.3247	
	3	0.3983	0.4003	0.3961	0.3304	0.3349	0.3892	0.3632	0.3852	0.3612	0.3610	0.3574	0.3643	0.3670	0.3303	0.3689	
	4	0.3976	0.4008	0.3917	0.2919	0.2967	0.3666	0.3452	0.3723	0.3536	0.3530	0.3393	0.3485	0.3522	0.3535	0.3535	
	5	0.4299	0.4344	0.4239	0.2993	0.3061	0.3821	0.3718	0.3981	0.3831	0.3826	0.3572	0.3717	0.3760	0.3911	0.3600	
	6	0.4839	0.4903	0.4763	0.3058	0.3198	0.4029	0.4051	0.4321	0.4193	0.4180	0.3832	0.4055	0.4153	0.3947	0.3903	
	7	0.5628	0.5711	0.5561	0.3552	0.3743	0.4568	0.4729	0.4962	0.4890	0.4888	0.4428	0.4717	0.4850	0.4073	0.4515	
	8	0.6113	0.6209	0.6122	0.3851	0.4124	0.5050	0.5352	0.5512	0.5432	0.5446	0.4937	0.5201	0.5281	0.4496	0.4774	
	9	0.6755	0.6855	0.6767	0.4166	0.4516	0.5535	0.5944	0.6034	0.5934	0.5914	0.5329	0.5699	0.5795	0.4627	0.5042	
	10	0.7206	0.7318	0.7208	0.4159	0.4553	0.5713	0.6249	0.6300	0.6238	0.6183	0.5506	0.5946	0.6080	0.4345	0.5098	
	11	0.7950	0.8058	0.7928	0.4377	0.4834	0.6313	0.6863	0.6833	0.6796	0.6736	0.6052	0.6493	0.6641	0.4822	0.5520	
	12	0.8531	0.8645	0.8499	0.4432	0.4963	0.6675	0.7443	0.7322	0.7324	0.7246	0.6508	0.6922	0.7043	0.5374	0.5471	
Ratio of RMSE VS VAR																	
h	1	1.0000	1.0042	0.9982	0.9083	0.9083	0.9870	0.9329	0.9853	0.9319	0.9290	0.9144	0.9350	0.9452	0.7611	0.9161	
	2	1.0000	1.0047	0.9982	0.9037	0.9103	1.0378	0.9736	1.0256	0.9493	0.9462	0.9582	0.9553	0.9441	0.8933	0.9098	
	3	1.0000	1.0051	0.9944	0.8295	0.8409	0.9771	0.9117	0.9670	0.9068	0.9062	0.8972	0.9145	0.9213	0.8291	0.9260	
	4	1.0000	1.0080	0.9852	0.7341	0.7463	0.9221	0.8682	0.9363	0.8894	0.8878	0.8535	0.8765	0.8859	0.8892	0.8890	
	5	1.0000	1.0105	0.9860	0.6963	0.7121	0.8888	0.8649	0.9260	0.8910	0.8899	0.8310	0.8647	0.8747	0.9097	0.8374	
	6	1.0000	1.0133	0.9842	0.6320	0.6609	0.8327	0.8371	0.8930	0.8665	0.8638	0.7920	0.8379	0.8583	0.8156	0.8066	
	7	1.0000	1.0147	0.9880	0.6312	0.6651	0.8117	0.8403	0.8816	0.8689	0.8685	0.7868	0.8381	0.8617	0.7237	0.8022	
	8	1.0000	1.0157	1.0015	0.6299	0.6746	0.8260	0.8755	0.9017	0.8885	0.8909	0.8076	0.8509	0.8639	0.7355	0.7810	
	9	1.0000	1.0148	1.0018	0.6168	0.6687	0.8195	0.8800	0.8933	0.8786	0.8755	0.7889	0.8437	0.8580	0.6850	0.7465	
	10	1.0000	1.0156	1.0003	0.5772	0.6318	0.7929	0.8673	0.8743	0.8656	0.8581	0.7641	0.8251	0.8437	0.6029	0.7075	
	11	1.0000	1.0135	0.9972	0.5506	0.6081	0.7941	0.8632	0.8595	0.8549	0.8473	0.7612	0.8168	0.8353	0.6065	0.6943	
	12	1.0000	1.0135	0.9963	0.5195	0.5818	0.7824	0.8725	0.8583	0.8586	0.8494	0.7629	0.8115	0.8257	0.6299	0.6414	
Ratio of RMSE VS AR																	
h	1	1.0916	1.0962	1.0896	0.9915	0.9915	1.0775	1.0183	1.0756	1.0173	1.0141	0.9982	1.0207	1.0318	0.8308	1.0000	
	2	1.0991	1.1042	1.0971	0.9932	1.0005	1.1407	1.0701	1.1273	1.0434	1.0400	1.0532	1.0499	1.0376	0.9819	1.0000	
	3	1.0799	1.0853	1.0738	0.8957	0.9080	1.0551	0.9845	1.0442	0.9792	0.9786	0.9688	0.9876	0.9949	0.8954	1.0000	
	4	1.1249	1.1339	1.1082	0.8258	0.8395	1.0372	0.9766	1.0532	1.0005	0.9986	0.9601	0.9859	0.9965	1.0002	1.0000	
	5	1.1942	1.2067	1.1774	0.8315	0.8504	1.0614	1.0328	1.1058	1.0641	1.0628	0.9923	1.0326	1.0445	1.0863	1.0000	
	6	1.2397	1.2562	1.2201	0.7835	0.8193	1.0323	1.0377	1.1071	1.0743	1.0709	0.9818	1.0387	1.0641	1.0111	1.0000	
	7	1.2466	1.2649	1.2316	0.7868	0.8291	1.0118	1.0475	1.0990	1.0832	1.0827	0.9808	1.0447	1.0742	0.9021	1.0000	
	8	1.2804	1.3005	1.2823	0.8065	0.8638	1.0577	1.1209	1.1545	1.1377	1.1407	1.0341	1.0894	1.1061	0.9417	1.0000	
	9	1.3396	1.3595	1.3421	0.8262	0.8958	1.0978	1.1789	1.1968	1.1770	1.1729	1.0569	1.1302	1.1494	0.9176	1.0000	
	10	1.4135	1.4356	1.4140	0.8158	0.8931	1.1208	1.2259	1.2358	1.2236	1.2129	1.0801	1.1663	1.1926	0.8522	1.0000	
	11	1.4402	1.4597	1.4363	0.7929	0.8758	1.1437	1.2433	1.2379	1.2312	1.2204	1.0964	1.1763	1.2031	0.8735	1.0000	
	12	1.5591	1.5801	1.5533	0.8100	0.9071	1.2199	1.3603	1.3382	1.3386	1.3244	1.1895	1.2652	1.2873	0.9821	1.0000	

**Table 2.2 RMSE of Out-of-sample Forecast of CPI from FAVAR (M=1) model:**

FAVAR (M=1)		K	AR	1	2	3	4	5	6	7	8	9	10	avg K=1~10	avg K=1~3	avg K=1~2
cpi																
lags=1																
K=0~10 h=1~12																
h	1	0.3077	0.3147	0.3326	0.2966	0.2979	0.3139	0.2961	0.3118	0.2965	0.2976	0.3107	0.2987	0.3051	0.3223	
	2	0.3247	0.3319	0.3531	0.3131	0.3139	0.3422	0.3173	0.3352	0.3088	0.3078	0.3300	0.3172	0.3228	0.3412	
	3	0.3689	0.3773	0.4008	0.3258	0.3276	0.3588	0.3257	0.3481	0.3262	0.3258	0.3384	0.3399	0.3585	0.3878	
	4	0.3535	0.3662	0.3969	0.2839	0.2866	0.3236	0.2891	0.3165	0.3013	0.3013	0.3113	0.3122	0.3386	0.3800	
	5	0.3600	0.3781	0.4293	0.2899	0.2943	0.3304	0.2946	0.3226	0.3109	0.3130	0.3160	0.3212	0.3543	0.4023	
	6	0.3903	0.4154	0.4837	0.2979	0.3090	0.3423	0.3037	0.3037	0.3301	0.3226	0.3264	0.3404	0.3881	0.4483	
	7	0.4515	0.4831	0.5632	0.3481	0.3641	0.3919	0.3582	0.3802	0.3812	0.3878	0.3815	0.3991	0.4532	0.5218	
	8	0.4774	0.5135	0.6173	0.3757	0.3974	0.4275	0.3956	0.4147	0.4162	0.4281	0.4243	0.4334	0.4881	0.5642	
	9	0.5042	0.5487	0.6760	0.3993	0.4256	0.4576	0.4238	0.4383	0.4112	0.4463	0.4433	0.4605	0.5246	0.6112	
	10	0.5098	0.5687	0.7189	0.3950	0.4255	0.4660	0.4336	0.4448	0.4522	0.4522	0.4475	0.4685	0.5416	0.6425	
	11	0.5520	0.6187	0.7856	0.4078	0.4431	0.4999	0.4641	0.4686	0.4781	0.4754	0.4853	0.5004	0.5845	0.7001	
	12	0.5471	0.6311	0.8335	0.4001	0.4408	0.5111	0.4778	0.4756	0.4878	0.4829	0.4978	0.5072	0.6009	0.7305	
Ratio of RMSE VS AR																
h	1	1.0000	1.0229	1.0810	0.9641	0.9682	1.0202	0.9623	1.0133	0.9638	0.9674	1.0099	0.9709	0.9918	1.0477	
	2	1.0000	1.0223	1.0874	0.9643	0.9666	1.0538	0.9770	1.0322	0.9508	0.9479	1.0163	0.9767	0.9941	1.0509	
	3	1.0000	1.0230	1.0866	0.8833	0.8881	0.9727	0.8830	0.9437	0.8842	0.8833	0.9173	0.9214	0.9720	1.0512	
	4	1.0000	1.0360	1.1229	0.8032	0.8110	0.9156	0.8178	0.8954	0.8523	0.8525	0.8808	0.8832	0.9581	1.0751	
	5	1.0000	1.0503	1.1924	0.8052	0.8176	0.9178	0.8183	0.8961	0.8636	0.8694	0.8778	0.8922	0.9842	1.1175	
	6	1.0000	1.0643	1.2392	0.7633	0.7917	0.8768	0.7781	0.7781	0.8456	0.8264	0.8362	0.8720	0.9942	1.1485	
	7	1.0000	1.0700	1.2474	0.7710	0.8064	0.8680	0.7933	0.8421	0.8442	0.8588	0.8450	0.8839	1.0037	1.1557	
	8	1.0000	1.0756	1.2930	0.7869	0.8325	0.8954	0.8286	0.8685	0.8718	0.8967	0.8887	0.9077	1.0224	1.1818	
	9	1.0000	1.0883	1.3406	0.7919	0.8441	0.9075	0.8405	0.8694	0.8155	0.8852	0.8792	0.9134	1.0405	1.2122	
	10	1.0000	1.1157	1.4102	0.7749	0.8348	0.9141	0.8506	0.8725	0.8871	0.8870	0.8779	0.9190	1.0624	1.2603	
	11	1.0000	1.1208	1.4232	0.7387	0.8028	0.9057	0.8407	0.8490	0.8661	0.8612	0.8792	0.9066	1.0589	1.2683	
	12	1.0000	1.1534	1.5234	0.7312	0.8056	0.9341	0.8733	0.8692	0.8915	0.8825	0.9097	0.9270	1.0983	1.3352	

**Table 3.1 RMSE of Out-of-sample Forecast of Unemployment Rate from FAVAR (M=3) model:**

FAVAR (M=3) unemp lags=1 K=0~10 h=1~12	K	VAR	1	2	3	4	5	6	7	8	9	10	avg K=1~10	avg K=1~3	avg K=1~2	AR
h	1	0.1065	0.1079	0.1040	0.1131	0.1113	0.1249	0.1412	0.1402	0.1473	0.1488	0.1224	0.1197	0.1079	0.1055	0.1239
	2	0.1102	0.1120	0.1094	0.1226	0.1212	0.1479	0.1617	0.1605	0.1730	0.1737	0.1423	0.1405	0.1224	0.1192	0.1305
	3	0.1332	0.1360	0.1237	0.1481	0.1409	0.2156	0.2573	0.2496	0.2626	0.2756	0.2161	0.1647	0.1407	0.1367	0.1971
	4	0.1418	0.1448	0.1340	0.1653	0.1648	0.2583	0.3007	0.2929	0.3110	0.3213	0.2523	0.1999	0.1711	0.1665	0.2076
	5	0.1671	0.1670	0.1446	0.1850	0.1810	0.3289	0.4043	0.3874	0.4048	0.4291	0.3417	0.2189	0.1855	0.1803	0.2799
	6	0.1776	0.1760	0.1558	0.2025	0.2069	0.3931	0.4652	0.4496	0.4715	0.4951	0.3917	0.2288	0.1885	0.1822	0.2860
	7	0.1731	0.1613	0.1271	0.1886	0.1937	0.4574	0.5702	0.5457	0.5656	0.6047	0.4826	0.2407	0.1939	0.1872	0.3460
	8	0.1922	0.1769	0.1447	0.2137	0.2307	0.5384	0.6657	0.6452	0.6692	0.7072	0.5671	0.2566	0.2027	0.1953	0.3569
	9	0.2049	0.1665	0.1233	0.2182	0.2396	0.6290	0.8072	0.7777	0.8002	0.8540	0.6933	0.2572	0.1928	0.1839	0.4308
	10	0.2396	0.1931	0.1454	0.2637	0.2956	0.7719	0.9599	0.9387	0.9620	1.0143	0.8324	0.2637	0.1849	0.1742	0.4558
	11	0.2387	0.1878	0.0946	0.2694	0.3199	0.9013	1.1632	1.1289	1.1548	1.2094	1.0018	0.2919	0.2000	0.1881	0.5697
	12	0.3073	0.2482	0.1552	0.3539	0.4116	1.1076	1.3963	1.3729	1.3950	1.4432	1.2156	0.3138	0.2051	0.1905	0.6234
Ratio of RMSE VS VAR																
h	1	1.0000	1.0137	0.9772	1.0619	1.0452	1.1729	1.3267	1.3170	1.3833	1.3977	1.1497	1.1242	1.0133	0.9911	1.1638
	2	1.0000	1.0163	0.9923	1.1122	1.0994	1.3420	1.4670	1.4565	1.5700	1.5762	1.2914	1.2743	1.1106	1.0813	1.1838
	3	1.0000	1.0209	0.9288	1.1119	1.0574	1.6183	1.9317	1.8740	1.9715	2.0688	1.6224	1.2365	1.0563	1.0260	1.4799
	4	1.0000	1.0212	0.9449	1.1658	1.1618	1.8212	2.1206	2.0654	2.1929	2.2654	1.7788	1.4096	1.2064	1.1740	1.4639
	5	1.0000	0.9989	0.8650	1.1069	1.0829	1.9676	2.4186	2.3178	2.4217	2.5673	2.0442	1.3097	1.1099	1.0787	1.6746
	6	1.0000	0.9908	0.8769	1.1401	1.1649	2.2127	2.6190	2.5312	2.6541	2.7875	2.2049	1.2879	1.0610	1.0256	1.6103
	7	1.0000	0.9317	0.7341	1.0896	1.1188	2.6417	3.2937	3.1517	3.2666	3.4927	2.7876	1.3902	1.1197	1.0812	1.9986
	8	1.0000	0.9203	0.7528	1.1117	1.2004	2.8014	3.4640	3.3570	3.4818	3.6794	2.9507	1.3349	1.0544	1.0160	1.8571
	9	1.0000	0.8123	0.6017	1.0648	1.1690	3.0694	3.9387	3.7950	3.9047	4.1673	3.3831	1.2549	0.9410	0.8972	2.1022
	10	1.0000	0.8062	0.6068	1.1008	1.2340	3.2218	4.0069	3.9183	4.0155	4.2338	3.4747	1.1007	0.7720	0.7269	1.9027
	11	1.0000	0.7865	0.3961	1.1285	1.3400	3.7751	4.8722	4.7286	4.8371	5.0658	4.1962	1.2226	0.8375	0.7879	2.3864
	12	1.0000	0.8078	0.5050	1.1516	1.3393	3.6044	4.5439	4.4678	4.5397	4.6965	3.9559	1.0213	0.6674	0.6199	2.0287
Ratio of RMSE VS AR																
h	1	0.8592	0.8710	0.8396	0.9124	0.8981	1.0078	1.1400	1.1316	1.1886	1.2010	0.9879	0.9659	0.8707	0.8516	1.0000
	2	0.8447	0.8585	0.8382	0.9395	0.9287	1.1336	1.2392	1.2303	1.3262	1.3315	1.0909	1.0764	0.9382	0.9134	1.0000
	3	0.6757	0.6899	0.6276	0.7513	0.7145	1.0935	1.3053	1.2663	1.3322	1.3979	1.0963	0.8355	0.7138	0.6933	1.0000
	4	0.6831	0.6976	0.6455	0.7964	0.7936	1.2441	1.4486	1.4109	1.4980	1.5475	1.2151	0.9629	0.8241	0.8020	1.0000
	5	0.5971	0.5965	0.5165	0.6610	0.6467	1.1749	1.4443	1.3840	1.4461	1.5330	1.2207	0.7821	0.6628	0.6442	1.0000
	6	0.6210	0.6153	0.5446	0.7080	0.7234	1.3741	1.6264	1.5718	1.6482	1.7310	1.3692	0.7998	0.6589	0.6369	1.0000
	7	0.5003	0.4662	0.3673	0.5452	0.5598	1.3217	1.6480	1.5769	1.6344	1.7476	1.3947	0.6956	0.5603	0.5410	1.0000
	8	0.5385	0.4956	0.4054	0.5986	0.6464	1.5085	1.8653	1.8077	1.8749	1.9813	1.5889	0.7188	0.5678	0.5471	1.0000
	9	0.4757	0.3864	0.2862	0.5065	0.5561	1.4601	1.8736	1.8052	1.8574	1.9823	1.6093	0.5969	0.4476	0.4268	1.0000
	10	0.5256	0.4237	0.3189	0.5785	0.6486	1.6932	2.1058	2.0593	2.1104	2.2251	1.8262	0.5785	0.4057	0.3820	1.0000
	11	0.4190	0.3296	0.1660	0.4729	0.5615	1.5820	2.0417	1.9815	2.0270	2.1228	1.7584	0.5123	0.3510	0.3302	1.0000
	12	0.4929	0.3982	0.2489	0.5677	0.6602	1.7767	2.2398	2.2023	2.2377	2.3150	1.9500	0.5034	0.3290	0.3056	1.0000

**Table 3.2 RMSE of Out-of-sample Forecast of Unemployment Rate from FAVAR (M=1) model:**

FAVAR (M=1) unemp lags=13 K=0~10 h=1~12	K	AR	1	2	3	4	5	6	7	8	9	10	avg K=1~10 lags=1	avg K=1~3	avg K=1~2
h	1	0.1239	0.1219	0.0965	0.1086	0.1115	0.1332	0.1563	0.1476	0.1469	0.1535	0.1266	0.1240	0.0939	0.1018
	2	0.1305	0.1261	0.0985	0.1131	0.1169	0.1532	0.1746	0.1670	0.1696	0.1793	0.1487	0.1429	0.1191	0.1225
	3	0.1971	0.1840	0.0983	0.1243	0.1288	0.2245	0.2774	0.2576	0.2530	0.2705	0.2232	0.1687	0.1424	0.1444
	4	0.2076	0.1913	0.1061	0.1378	0.1479	0.2623	0.3197	0.3023	0.2947	0.3146	0.2609	0.2037	0.1704	0.1754
	5	0.2799	0.2429	0.1286	0.1572	0.1694	0.3405	0.4287	0.3992	0.3916	0.4182	0.3565	0.2251	0.1944	0.1985
	6	0.2860	0.2432	0.1358	0.1757	0.1939	0.4028	0.4903	0.4676	0.4508	0.4793	0.4081	0.2362	0.2040	0.2053
	7	0.3460	0.2722	0.1354	0.1726	0.2027	0.4831	0.6059	0.5711	0.5554	0.5820	0.5000	0.2502	0.2057	0.2095
	8	0.3569	0.2713	0.1488	0.2106	0.2458	0.5635	0.7040	0.6824	0.6524	0.6785	0.5855	0.2690	0.2170	0.2258
	9	0.4308	0.2782	0.1659	0.2498	0.2973	0.6806	0.8633	0.8278	0.8006	0.8275	0.7151	0.2731	0.2193	0.2320
	10	0.4558	0.2830	0.1802	0.3200	0.3712	0.8250	1.0196	1.0025	0.9540	0.9784	0.8569	0.2870	0.2255	0.2458
	11	0.5697	0.3287	0.2023	0.3772	0.4469	0.9857	1.2459	1.2089	1.1647	1.1815	1.0334	0.3225	0.2398	0.2728
	12	0.6234	0.3428	0.2243	0.4912	0.5630	1.1952	1.4830	1.4686	1.3954	1.4137	1.2531	0.3520	0.2269	0.2780
Ratio of RMSE VS AR															
h	1	1.0000	0.9839	0.7790	0.8766	0.9002	1.0749	1.2614	1.1916	1.1858	1.2386	1.0215	1.0004	0.7577	0.8215
	2	1.0000	0.9667	0.7548	0.8665	0.8960	1.1740	1.3383	1.2801	1.2994	1.3741	1.1397	1.0953	0.9125	0.9391
	3	1.0000	0.9333	0.4986	0.6304	0.6532	1.1388	1.4073	1.3069	1.2833	1.3723	1.1322	0.8558	0.7225	0.7325
	4	1.0000	0.9213	0.5112	0.6638	0.7123	1.2636	1.5400	1.4561	1.4198	1.5153	1.2567	0.9814	0.8209	0.8447
	5	1.0000	0.8678	0.4595	0.5615	0.6052	1.2166	1.5316	1.4260	1.3991	1.4942	1.2738	0.8043	0.6945	0.7093
	6	1.0000	0.8503	0.4749	0.6144	0.6780	1.4081	1.7140	1.6347	1.5760	1.6755	1.4267	0.8257	0.7132	0.7177
	7	1.0000	0.7867	0.3913	0.4988	0.5859	1.3962	1.7510	1.6504	1.6050	1.6819	1.4451	0.7230	0.5944	0.6054
	8	1.0000	0.7602	0.4168	0.5901	0.6887	1.5787	1.9725	1.9118	1.8280	1.9010	1.6406	0.7538	0.6081	0.6327
	9	1.0000	0.6457	0.3852	0.5798	0.6900	1.5798	2.0038	1.9215	1.8584	1.9207	1.6600	0.6339	0.5089	0.5384
	10	1.0000	0.6208	0.3952	0.7019	0.8144	1.8098	2.2367	2.1992	2.0929	2.1464	1.8798	0.6295	0.4948	0.5393
	11	1.0000	0.5769	0.3551	0.6621	0.7844	1.7301	2.1869	2.1219	2.0443	2.0738	1.8139	0.5661	0.4209	0.4788
	12	1.0000	0.5499	0.3598	0.7880	0.9031	1.9172	2.3789	2.3558	2.2384	2.2677	2.0101	0.5646	0.3640	0.4459

## Appendix 1: Data Description

All series were downloaded from Bloomberg except for Gross Capital Formation which was downloaded from the website of Hong Kong Census and Statistics Department.

The transformation codes are: lv = level of the data, ln= natural log,  $\Delta$  = first difference,  $\Delta^2$  = second difference. Fast or slow-moving series in the estimation are indicated by F or S respectively.

Mnemonic	Description	Transform	Fast or Slow?
<b>Real Income and Activities</b>			
1 RGDP	GDP growth rate (chained 2005) yoy %	lv	S
2 INVEST	Gross Capital Formation (chained 2005) yoy %	lv	S
3 PI	HK Real wage index of all industry sectors yoy %	lv	S
4 CONSUM	HK Private consumption (chained 2005) yoy %	lv	S
5 IMP	HK Imports yoy %	$\Delta$ ln	S
6 EXP	HK Exports yoy %	lv	S
7 DOEXP	HK Domestic Exports yoy %	lv	S
8 REXP	HK Re-exports yoy %	lv	S
9 RS	HK Retail sales value yoy (2004-2005=100) yoy %	lv	S
10 WSALE	HK Business receipts - wholesale/retail (2000=100) yoy %	lv	S
11 IMPEXP	HK Business receipts - import/export trade (2000=100) yoy %	lv	S
12 RESTAU	HK Business receipts - restaurant (2000=100) yoy %	lv	S
13 HOTEL	HK Business receipts - hotel (2000=100) yoy %	lv	S
14 BANKING	HK Business receipts - banking (2000=100) yoy %	lv	S
15 FINANCE	HK Business receipts - financial services exclude banking (2000=100) yoy %	lv	S
16 INSUR	HK Business receipts - insurance (2000=100) yoy %	lv	S
17 REALEST	HK Business receipts - real estate (2000=100) yoy %	lv	S
18 BUSSER	HK Business receipts - business services (2000=100) yoy %	lv	S

19 TOUR	HK Business receipts - tourism/convention/exhibition (2000=100) yoy %	lv	S
20 IT	HK Business receipts - computer/information services (2000=100) yoy %	lv	S
21 IP	HK Industrial Production yoy %	lv	S
<b>Housing Market</b>			
22 PROP	HK Property sale & purchase agreements - total	$\Delta$ ln	F
23 RESID	HK Property sale & purchase agreements - residential	$\Delta$ ln	F
24 NONRESID	HK Property sale & purchase agreements - non-residential	$\Delta$ ln	F
25 RESIPRICE	HK Residential price index	$\Delta^2$ ln	F
<b>Labor Market</b>			
26 UNEMP	HK Unemployment rate % SA	$\Delta$ lv	S
27 PARTIP	HK Labor force participation rate %	$\Delta$ lv	S
28 LABORFORCE	HK Labor force yoy %	$\Delta^2$ lv	S
29 EMMANUF	HK Employment - manufacturing (thousand)	$\Delta$ ln	S
30 EMCONSTRUC	HK Employment - construction (thousand)	$\Delta$ ln	S
31 EMRETAIL	HK Employment - wholesale/retail (thousand)	$\Delta$ ln	S
32 EMTRANSPORT	HK Employment - transport/storage (thousand)	$\Delta$ ln	S
33 EMFINANCE	HK Employment - financial services (thousand)	$\Delta$ ln	S
34 EMSOCIAL	HK Employment - community/social services (thousand)	$\Delta$ ln	S
<b>Money and Exchange Rate</b>			
35 M1	HK M1 yoy % (chained 2005)	$\Delta$ lv	F
36 M2	HK M2 yoy % (chained 2005)	$\Delta$ lv	F
37 M3	HK M3 yoy % (chained 2005)	$\Delta$ lv	F
38 FXRES	HK Foreign Currency Reserve Assets (bln USD) (chained 2005)	$\Delta^2$ ln	F
39 FXRESFOR	HK Exchange Fund - Foreign Currency Assets (bln HKD) (chained 2005)	$\Delta^2$ ln	F
40 FXRESHK	HK Exchange Fund - HKD Assets (bln HKD) (chained 2005)	$\Delta^2$ ln	F
41 HKDEFF	HK dollar effective exchange rate index	$\Delta$ ln	F
42 USD	HK dollar per US dollar exchange rate	$\Delta$ ln	F
43 JPY	Yen per US dollar exchange rate	$\Delta$ ln	F
44 GBP	US dollar per British pound exchange rate	$\Delta$ ln	F
45 CHF	Swiss francs per US dollar exchange rate	$\Delta$ ln	F

**Price Levels**

46 PPI	HK PPI yoy %	$\Delta$ lv	F
47 CPI	HK CPI yoy%	$\Delta$ lv	F
48 CPIA	HK CPI A yoy%	$\Delta$ lv	F
49 CPIB	HK CPI B yoy%	$\Delta$ lv	F
50 CPIC	HK CPI C yoy%	$\Delta$ lv	F

**Loans, Deposits and Interest Rates**

51 LOAN	HK Total loans balances yoy %	$\Delta^2$ ln	F
52 DEPOSIT	HK Deposits (HKD + Foreign Currency)	$\Delta^2$ ln	F
53 HKDEPRMB	HK RMB deposits (HKD + Foreign Currency)	$\Delta^2$ ln	F
54 PRIME	HK Prime rate HSBC	$\Delta$ lv	F
56 HIB1M	HIBOR 1 month	$\Delta$ lv	F
57 HIB3M	HIBOR 3 month	$\Delta$ lv	F
58 HIB6M	HIBOR 6 month	$\Delta$ lv	F
59 HIB12M	HIBOR 12 month	$\Delta$ lv	F
61 PH1M	Prime-HIBOR 1M spread	$\Delta$ lv	F
62 PH3M	Prime-HIBOR 3M spread	$\Delta$ lv	F
63 PH6M	Prime-HIBOR 6M spread	$\Delta$ lv	F
64 PH12M	Prime-HIBOR 12M spread	$\Delta$ lv	F

**Stock Market**

63 HSI	Hang Seng Index	$\Delta^2$ ln	F
64 HSHR	H-Share Index	$\Delta^2$ ln	F
65 HSITURN	Hang Seng Index turnover (bln HKD)	$\Delta^2$ ln	F

**China**

66 CGDP	China Real GDP yoy %	lv	S
67 CNIMP	China Imports yoy %	lv	S
68 CNEXP	China Exports yoy %	lv	S
69 CNCPI	China CPI - Urban	$\Delta$ lv	F
70 CNFXRES	China foreign exchange reserve (bln USD)	$\Delta^2$ ln	F
71 CNLENDRT	China 1 yr Best Lending Rate	$\Delta$ lv	F
72 RMB	RMB per USD	$\Delta$ ln	F

**U.S.**

73 USFFR	U.S. Fed Funds Target Rate	$\Delta$ ln	F
74 US3MT	U.S. 3-month Treasury Yield	$\Delta$ ln	F
75 USGDP	U.S. GDP Chained 2000 Dollars yoy % SA	lv	S
76 USTRAD	U.S. Trade Balance Balance of Payments (bln USD) SA	$\Delta^2$ ln	S