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Abstract

This paper surveys the recent literature on inflation forecasting and conducts an extensive empirical analysis on forecasting inflation in Singapore, Japan, South Korea and Hong Kong paying particular attention to whether the inflation-markup theory can help to forecast inflation. We first review the relative performance of different predictors in forecasting h-quarter ahead inflation using single equations. These models include the autoregressive model and bivariate Philips curve models. The predictors are selected from business activity, financial activity, trade activity, labour market, interest rate market, money market, exchange rate market and global commodity market variables. We then evaluate a vector autoregressive inflation-markup model against the single equation models to understand whether there is any gain in forecasting using the inflation-markup theory. The paper subsequently analyses the robustness of these results by examining different forecasting procedures in the presence of structural breaks. Empirical results suggest that inflation in Singapore, Hong Kong and South Korea is best predicted by financial and business activity variables. For Japan, global commodity variables provide the most predictive content for inflation. In general, monetary variables tend to perform poorly. These results hold even when structural break is taken into consideration. The vector autoregressive inflation-markup model does improve on single equation models as forecasting horizon increases and these gains are found to be significant for Japan and Korea.

JEL Classification Codes: C32, C53, E31

Keywords: Inflation, Markup, Forecasting, Asia, Structural Break

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1 Introduction

With the rapid development in the real economies, central banks require good inflation forecasts in order to achieve price stability and sustainable economic growth. This is imperative as formulation and implementation of monetary policy weighs heavy on how inflation pans out into the future. This paper hopes to share some insights on this complex issue.

We take as our starting point the study by Stock and Watson (1999) in which the authors used a modified Philips curve with different predictors to study whether forecasting gains could be made compared to the autoregressive model. They found that housing starts, capacity utilisation and trade sales to be helpful for predicting one year ahead US inflation. They also found combining forecast further improves the forecast and created an activity index which was deemed the best predictor of US inflation. Atkeson and Ohanian (2001) however refuted this argument, claiming that the autoregressive model works better as it is more robust since different predictors only outperform the autoregressive model periodically. Extensions in inflation forecasting have been made in recent years. Goodhart and Hofmann (2000) and D'Agostino and Surico (2009) found asset prices such as housing price and global liquidity to be helpful predictors of US inflation. Banerjee and Marcellino (2005) and Arratibel and Kamps (2009) examined the relevance of predictors in forecasting inflation in Europe and Eastern Europe respectively. They found that labor and price variables contain predictive information. Thus, it is widely accepted that using correct predictors in a Phillips curve setting does improve on the autoregressive model.

More recently, the inflation-markup theory has gained ground in modelling and forecasting prices and wages due to its theoretical relevance and empirical success. The inflation-markup theory studies the relationship between prices and markups where markups are defined to be a ratio of price to cost. Research by Rotemberg and Woodford (1991) first showed that markups are countercyclical in general and thus negatively related to price increment. They assume that imperfectly competitive firms are unable to raise prices to offset rising cost due to inflation as firms may lose market share doing so. Cockerell and Russell (1995) using similar arguments found similar negative relation from a labor-wage point of view. They applied the Layard-Nickell labor-wage model which depends on the bargaining power of firms and labor. Their empirical success in modelling inflation in Australia from 1971 to 1994 led to further work by Banerjee and Russell (2001) who found it useful for modelling inflation in G7 nations. Sekine (2001) and Russell and Banerjee (2006) then applied the inflation-markup theory for forecasting inflation in Japan and EU respectively. They found that forecasts from the inflation-markup model improve on the forecasts from the Philips curve model. Thus, we also consider whether the inflation-markup model is useful for forecasting inflation in Asia.

In this paper, we evaluate the predictive content of a range of variables in forecasting inflation in Singapore, Japan, South Korea and Hong Kong and we evaluate the inflation-markup model to see if it provides significantly better forecasts. We then check for the robustness of these results taking structural breaks into consideration. To date, this is the first systematic study on the informational contents of predictors from business activities, financial activities, trade activities, labour markets, interest rate markets, money markets, exchange rate markets and global commodity markets in forecasting inflation in these countries.

Our analysis leads to the following main conclusions. First, for financial centres such as Singapore and Hong Kong, financial variables such as asset prices perform well in forecasting inflation. This is in comparison to import or resource dependent nations such as Japan where global commodity prices are helpful. For highly industrialised nations like South Korea, unemployment and business related outputs have predictive ability. More interestingly, dividend yield seem to predict inflation well across different economies as the forecast horizon increases. This is widely discussed as the 'Fed Model' where dividend yields correlate with bond yields which act as a proxy for expected future inflation.

Second, although forecasting techniques such as aggregating forecasts or aggregating information improves inflation forecasts, the small scale Vector Autoregressive (VAR) model using inflation-markup theory outperforms the former when forecasting horizon increases. This is evident in Japan and South Korea when forecasts are made two years ahead.

Third, the results for predictors that are found to be useful in forecasting inflation are in general robust to structural break. We applied the expanding window forecasting procedure and the structural break robust forecasting procedure and found that predictors which worked well in our initial estimation and forecasting continued to do well.

The rest of the paper is organised as follows: the next section is a literature review on forecasting inflation. Section 3 describes how the data is managed and how the analysis is carried out. Section 4 presents and explains the results in depth and Section 5 evaluates the robustness of these results. Section 6 summarises and concludes.

2 Literature Review

This section reviews inflation forecasting with emphasis on the predictive content of different variables. The inflation-markup theory, where markup and inflation follows a long term relation, is also discussed. Inflation developments in Asia, which is infrequently analysed, is also examined with specific focus on Singapore, Japan, South Korea and Hong Kong.

2.1 Forecasting Inflation

Stock and Watson (1999) studied 189 different predictors in a modified bivariate Phillips curve to generate direct one year ahead forecast of inflation. They found housing starts, capacity utilisation and trade sales to be important predictors for USA as compared to unemployment. However, an extensive analysis showed that an activity index combining 61 activity variables predict inflation best. Further analysis by Goodhart and Hofmann (2000) and Stock and Watson (2003) focusing on using asset prices to predict US inflation showed asset prices to be mildly successful in forecasting inflation but the results are not robust to different forecast horizons. Banerjee and Marcellino (2005) and Arratibel and Kamps (2009) conducted similar studies for European countries. The results were found to be country specific with labor variables and price variables being useful predictors for most countries.

Atkeson and Ohanian (2001) conducted a simple survey to understand whether the unemployment and the activity index proposed by Stock and Watson in a Phillips curve setting is able to beat the autoregressive model in forecasting inflation. Their results showed that the atheoretical autoregressive model generally outperformed the bivariate Philips curve. Cecchetti and Chu (2001) lent support to this argument claiming that the autoregressive model is the most robust across different forecasting horizons. However, they also noted that the Phillips curve model using different predictors do improve on the autoregressive model in different horizons, that is, specific predictors are still useful for specific forecasting horizons.

Following this, there has been some recent interest in using "Markup" variables to forecast inflation. The inflation-markup theory in general relates a variant of markup to inflation. Markup variants include the ratio of price to marginal cost, business cost, wages or unit labor costs. Research by Cockerell and Russell (1995), De Brouwer and Ericsson (1998) and Banerjee and Russell (2005) amongst others focused an imperfectly-competitive macroeconomic model where inflation affects firms' markup negatively from a Layard-Nickell labor-wage bargaining tradition. Neiss (2001) and Klein (2011) however argued that such a relation could be positive depending on market structure and bargaining power of labor in different countries. More important to this model is the definition of markup. With this in mind, Sekine (2001) and Banerjee and Russell (2006) applied the markup of prices on unit labor cost in Japan and Europe respectively and found forecasting gains with respect to modified Philips curve forecasting.

2.2 Inflation in Asia

The four Asian nations in this paper are Singapore, Japan, South Korea and Hong Kong. The sample period for our study is 1978 to 2010. Singapore, South Korea and Hong Kong have achieved tremendous success in economic growth in the past 40 years. However, along with the success, inflation rates have also been higher and more volatile as compared to developed nations. Japan grew rapidly from 1960s to late-1980s before the crash in asset prices such as stocks and properties brought its economy to a standstill. Thus, inflation in Japan is mostly negative since mid-1990s. The differences in inflation could be partly due to differences in how the respective central banks operate.

The Monetary Authority of Singapore (MAS) adopts an active monetary strategy via exchange rate adjustments when necessary to stabilise inflation while generating sustainable economic growth. The Bank of Japan (BOJ) focuses instead on the yen and how it affects economic growth via export competitiveness. The Hong Kong Monetary Authority (HKMA) pursues currency and banking stability and links HKD to USD thus effectively forgoing monetary rule while the Bank of Korea (BOK) targeted inflation post the Asian Financial Crisis (AFC) to rein in price stability. Thus, it is unsurprising that inflation rates behave differently in these countries.

As shown in Figure 1, all four nations had similar periods where annualised quarterly inflation was relatively more volatile. The 4 main periods captured in our time frame are as listed: Energy Crisis in 1979, Asian Financial Crisis in 1997, Robust Economic Growth in 2007 and Global Financial Crisis (GFC) in 2009.

During the 1979 Energy Crisis, all four nations were affected due to their high reliance on oil imports. As shown in Figure 1, South Korea was most badly hit as quarterly inflation rose by more than 30%. This was followed by Japan and Singapore where oil plays an important role in energy generation thus affecting business costs. The Asian Financial Crisis in 1997 hit South Korea and Hong Kong hard. For Hong Kong, the real economy slowed, leading to a drastic fall in asset prices, resulting in falling consumer prices. For South Korea, rapid weakening of the Korean Won due to speculation led to higher raw material and fuel costs which fed into inflation. Japan and Singapore however remained relatively unscathed in that crisis. A period of stable prices ensued thereafter, with deflation occurring in Hong Kong and Japan due to currency adjustments after return to China and economic stagnation respectively. This happened until 2007 when prices in Asia began to climb. However, with the bursting of housing prices in USA, the Global Financial Crisis caused a sharp and sudden decline in growth and prices. In summary, from Table 1, Japan recorded the lowest rate of inflation and volatility while South Korea had the highest rate of inflation and volatility from 1978 to 2010. These series of events therefore provide a good platform for inflation modelling and forecasting.

Research on inflation dynamics and forecasting in Asia has however been sparse. In Japan, Sekine (2001) found that markups using Vector Autoregressive (VAR) models are negatively related to inflation and provides a good forecast of the latter when compared to autoregressive model. He found similar results using excess money and output gap. In Singapore, Chow and Choy (2009) found that a VAR model that including GDP growth, Consumer Price Index (CPI), world oil prices, world CPI and Nominal Effective Exchange Rate (NEER) helped predict inflation well. For Hong Kong, Hui and Yue (2006) found that asset prices, especially housing prices, model inflation well whereas Kim and Park (2006) presents evidence that controls on discount rates helped inflation targeting in Korea. This study hopes to provide further insights to inflation forecasting in the four economies above.

3 Data and Methodology

This section examines the data management procedures, specification of models and modelling and forecasting methods used in this paper.

3.1 Data Management

This paper collects up to 40 quarterly series for each country from 1978 to 2010 except for Hong Kong where data available starts at 1981. These data represents variables in business, financial, trade, labor, interest rate, money, exchange rate and global commodity markets and is listed in Table 1. The data are obtained mainly from the CEIC database. consumer price index was also rechecked with data given by individual monetary authority. The data were then subjected to a few data cleaning processes a follows: First, a few of the series contained large outliers and missing data points. In this case, these outliers were replaced with the average values proceeding and preceding it. Second, when data is available in monthly basis, these data were aggregated to quarterly observations through averages. Third, all data are transformed to be stationarity by taking first differences, second differences, logarithms or log-differences. This ensures that our regressions are not spurious since all variables are stationary. Tests on stationarity are conducted using Phillips-Perron unit root procedures as it corrects for heteroskedastic errors.

3.2 Single Equation Models

The Single Equation Models (SEMs) consist of statistical autoregressive model, bivariate Stock and Watson (SW) Philips curve models and multivariate combination models.

Multivariate combination models refer to forecast combination or information aggregation models. There is a fair amount if evidence suggesting that combining forecasts and aggregating information into a single forecast can produce better forecasts than individual forecasting models. There are many reasons for this phenomenal including the cancellation of opposite bias in different forecasts and reduction in bias due to structural breaks by aggregating models with different degree of structural stability. These and other issues are studied in depth by Hendry and Clements (2004) and Timmermann (2006).

One key issue lies in whether forecast combination or aggregating information in a works best. Hendry and Hubrich (2011) showed that for models with different stochastic structure but interdependencies amongst different variables, combining information works better than combining forecasts. Their empirical research on forecasting USA inflation supports the idea. It is, however, difficult to hypothesize about the data generating process of each model and thus most forecasters generally still use both forecast combination and multivariate regression models. The other issue lies in the procedures applied to generate these models as over-fitting would lead to misspecification which could thus worsen forecast performance. These procedures including using mean-weighted forecasting and forecast encompassing is examined in depth in Newbold and Harvey (2002) and Stock and Watson (2006).

In this analysis, an estimation window from 1978 to 2001 is used to provide forecast from 2002 to 2010. These windows are chosen as the estimated coefficients encompass inflation dynamics from the Energy Crisis and Asian Financial Crisis which could then allow for forecast evaluation during the period of Global Financial Crisis. The variable involved in our analysis is the annualised h-quarters ahead inflation which is given by $\pi_{t+h}^{h} = (400/h)(\log p_{t+h} - \log p_t)$. When h = 1, this is simply the annualised rate of quarterly inflation where p_t refers to the consumer price index. Due to the non-stationarity of h-quarters ahead inflation in some countries, the dependent variable in the estimation and forecast method is thus modified to $\pi_{t+h}^{h} - \pi_t$. This measures the annualised change in inflation h-quarters ahead with respect to current inflation.

Using the direct h-quarters ahead forecast, where h = 1, 4 and 8, the root mean square forecast error (RMSE) is then computed for forecasting evaluation purposes. The RMSE is given by:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(Y_{n,t+h}^{h} - F_{n,t+h}^{h}\right)^2}{n}} \qquad (1)$$

where $Y_{n,t+h}^{h}$ and $F_{n,t+h}^{h}$ represents real h-quarter ahead inflation and forecasted h-quarter ahead inflation respectively. For comparison purposes, the relative root mean square forecast error (RRMSE) was also computed, with the AR model being the benchmark.

3.2.1 Autoregressive Model

The univariate autoregression was proposed by Atkeson and Ohanian (2001) on grounds that future inflation is best predicted by current and past inflation and that inflation theories are not helpful in providing better forecast. In this case, the specification is given by

$$\pi_{t+h}^{h} - \pi_t = c + \gamma(L)\Delta\pi_t + e_{t+h} \qquad (2)$$

where $\gamma(L)$ is a polynomial in the lag operator L. In our application, this model is estimated recursively and includes, up to four lags, the best model being selected by the Schwarz Information Criterion (SIC). The SIC controls for the increase in explanatory power due to over-fitting by applying a penalty on the dimensionality of the model. The best chosen model is then used to forecast change in inflation in a direct manner.

3.2.2 Stock and Watson Phillips Curve

The Philips curve is a cornerstone macroeconomic theory linking inflation and unemployment. In general, an increase in demand for output leads to higher prices signalling producers to employ more workers to produce greater amount of output. This led to the famous trade-off between inflation and unemployment. However, stagflation in the 1970s raised questions about this theory.

Phelps (1967) and Friedman (1977) amongst others extended the classical model into the Non-Accelerating Inflation Rate of Unemployment (NAIRU) model. In the short run, the model is akin to the former but with added shifts in the long run as inflation expectation changes. In the long run, the economy returns back to its natural rate of unemployment. The NAIRU model is given by:

$$\Delta p_t = E_t(\Delta p_t^*) + \delta u_t + e_t \tag{3}$$

where variables are in logarithms and p_t, p_t^* and u_t represents logarithmic prices, expected prices and unemployment. Assuming backward looking adaptive expectations, $E_t(\Delta p_t^*) = p_{t-1}$. More generally, the Philips curve theory has recently been extended into a relation between inflation, lags of aggregate real activity and lags of past changes in inflation which Stock and Watson (1999) applied in their empirical study. The SW modified Philips curve is thus given by:

$$\pi_{t+h}^h - \pi_t = c + \beta(L)x_t + \gamma(L)\Delta\pi_t + e_{t+h} \tag{4}$$

where x_t represents a predictor variable. In this analysis, the change in annualised inflation h-quarters ahead is predicted using lags of the predictor variable and lags of changes in inflation. The specification assumes inflation is integrated of order one and that inflation and predictor variables are not cointegrated which is supported by research from Stock and

Watson (1999). Akin to previous section, estimation is done recursively allowing up to four lags for each lag polynomial in (5) and applying a HAC-OLS methodology. For each variable x_t, different transformation of the same variable is applied and only the transformation in the model with the lowest SIC is used for forecasting h-quarters ahead inflation.

3.2.3 Aggregating Forecast and Information

In line with forecasting gains in literature, forecasting with many predictors provides an excellent opportunity to exploit as much information content as possible to improve forecast accuracy. However, one cannot include all predictors as this would lead to over-fitting and biased estimation. Hence, it is important to use techniques to extract helpful information content for forecasting.

The first approach is to combine forecasts. This means that forecasts of inflation are made from models similar to equation (4) but with different predictors and an index of the forecast is constructed based on various weighting schemes. In this analysis, the equal forecast weighting scheme is employed. Stock and Watson (2006) found that the mean-weighted scheme does just as well as complicated schemes such as discounted RMSE weights and Time-Varying Parameters (TPV) weights. The specification employed is thus:

$$\pi^h_{t+h} - \pi_t = \frac{1}{n}\sum_{i=1}^{n} f_{i,t} + e_{t+h} \qquad (5)$$

where $f_{i,t}$ represents forecasts of change in h-quarters ahead inflation using predictor i at time t. Starting with the best forecast, the next best forecast is added to form a combination and the combination is evaluated based on root mean square error. If the newly combined forecast outperforms the previous, this combination remains and the third best forecast is once again combined. However, if the newly combined forecast underperforms the previous, this predictor's forecast is skipped and the next best is applied. This is done recursively until the top five predictors' forecasts are exhausted.

The second approach is to aggregate information by including predictors in a multivariate regression model instead. Normally, it would be advisable to pool or aggregate information rather than forecasts as the latter induces efficiency loss through its two stage estimation procedure. However, Diebold and Pauly (1990) recognised that this is sometimes impossible or too costly due to data constraints. In this analysis, data is available thus circumventing the issue. The focus is thus whether information should be combined. Chong and Hendry (1986) found that information should not be pooled if one forecasts encompasses the other which means that in all other cases, gains in forecasting could be possible.

Thus, the procedures taken in this analysis is first, identify individual predictors that gave best inflation forecast. Second, forecast encompassing test amongst two forecasts is carried out. If no single forecast encompasses the other, information is pooled. This means that the bivariate Stock and Watson Philips curve model is extended into a multivariate model. Similar to above sections, only multivariate model with lags that give rise to lowest SIC in estimation is applied to forecasting. If forecasting gains in terms of lower root mean square error is made when compared to individual forecasts, this combination remains and forecast encompassing test is repeated for the next best predictor. If forecasting gains are not made, the predictor is skipped. This is performed recursively until top five predictors are exhausted. The specification is thus:

$$\pi^h_{t+h} - \pi_t = c + \gamma(L)\Delta\pi_t + \alpha(L)y_{1,t} + ... + \eta(L)y_{5,t} + e_{t+h} \qquad (6)$$

where $y_{i,t}$ represents predictors i at time t, arranged from the smallest to largest RMSE. Results of these models are noted and used for comparison in the later sections.

3.3 Vector Autoregression Inflation-Markup Model

The inflation-markup theory has gained ground in recent years due to its theoretical relevance and empirical practicality. Research by Rotemberg and Woodford (1991) and Benabou (1992) applied general equilibrium models and found expressions relating inflation and markup on marginal cost. Cockerell and Russell (1995) and De Brouwer and Ericsson (1998) using similar arguments found a negative relationship from a labor-wage point of view instead and this was taken further by Banerjee and Cockerell (2001) and Banerjee and Russell (2001) who found it useful for understanding inflation in G7 nations. However, Klein (2011) showed otherwise in South Africa. More importantly, Banerjee and Russell (2006) amongst others applied it to inflation forecasting which outperforms the forecasting single equation models. This is the motivation for this analysis.

There are two main explanations for a negative relationship between markup and inflation. Firstly, marginal costs are difficult to allocate to jointly produce output, hence the profit maximising price is unknown. Firms believe they face an asymmetric loss function where setting a relatively high price leads to lesser profits in an imperfectly competitive market. Hence, firms act cautiously and set a price with a lower markup in times of inflation. Secondly, another reason for the negative relationship is that higher inflation would lead to a higher degree of search by consumers. Due to greater search, firms face a scenario of lowering markup in times of inflation. However, other studies suggest that markup could also be positively related to inflation. In this case, Phelps and Winter (1970) suggested that during inflationary phase, firms lower prices to expand the consumer base. However, there appears to be less support for this empirically.

The inflation-markup model applied in this analysis is developed from an imperfectly competitive macro-economic setting where inflation imposes cost on firms. In Layard-Nickell tradition, firm's desired markup is expressed as:

$$p - w = \omega_0 - \omega_1 U - \omega_2 \Delta U + \omega_3 z_p - \omega_4 (p - p^e) - \omega_5 \phi - \omega_6 \Delta p \tag{7}$$

while labor desired real wage is expressed as:

$$w - p = \beta_0 - \beta_1 U - \beta_2 \Delta U + \beta_3 z_w - \beta_4 (p - p^e) + \beta_5 \phi \tag{8}$$

where p, w, U, p^e, ϕ, z_p and z_w are prices, wages, unemployment rate, expected prices, productivity and shifts in bargaining position of firms and labor respectively. All variables are in logarithms and all coefficients are positive. For labor, z_w represents unemployment benefits, tax rates and labor market skill mismatches, while for firms, z_p represents market power, indirect taxes and non-labor costs. The unemployment term represents a measure of output in Okun's law. The cost of inflation to firm is $\omega_6 \Delta p$ and is positive assuming $\omega_6 > 0$.

By eliminating unemployment from (8) and (9) , assuming $\Delta U = 0$, p = p^e in the long run, firm's price independent of demand (ω_1 =0) and income shares independent of productivity in the long run, the expression relating markup and inflation reduces to:

$$mu = \omega_0 + \omega_3 z_p - \omega_6 \Delta p \tag{9}$$

Equation (9) shows that the relationship between inflation and markup is dependent on competitive economic environment z_p and that in general, if $\omega_6 > 0$, then markup of price on cost is inversely related to inflation. Further extension by Banerjee and Russell (2005) found a stable VAR inflation-markup model in the form of:

$$mu = q - \lambda \Delta p \tag{10}$$

where q and λ represent 'gross' markup and an inflation cost coefficient respectively. In most empirical studies, the markup is best defined as a ratio of price to the unit labor cost and the vector autoregression is chosen to capture linear dependencies amongst multivariate time series.

Our analysis of the inflation-markup model for forecasting begins with Equation (10). Two approaches are taken, with one being a direct method, while the other being an iterated method. The "direct" forecasts are made using a horizon specific estimated model, where the dependent variable is the multi-step ahead value being forecasted. This means, to forecast four quarters ahead inflation, we use π_{t+4}^{4} as one of the variables in the VAR. The "iterated" multi-step ahead forecasts are made using one period ahead model, iterated forward for the desired number of periods. This means, for a similar fixed estimation window, to obtain a four quarters ahead forecast, π_{t+4}^{4} , we first obtain forecasts π_{t+1}, π_{t+2}, π_{t+3} and π_{t+4}. From here, we sum the forecasts and convert it back to annualised terms. According to Marcellino, Stock and Watson (2006), the direct forecasting method is more robust to specification error while the iterated forecasting is more efficient and improves when forecasting horizon increases. For an unrestricted VAR, the specification is:

$$x_t = c + \sum_{i=1}^{4} \Pi x_{t-i} + e_t \tag{11}$$

where x_t represents the vector of variables of interest. For the direct approach, annualised h-quarters ahead inflation and the markup are the endogenous variables. The estimation period and forecasting period is similar to SEMs from 1978 to 2001 and 2002 to 2010 respectively. Starting with a model with four lags of both endogenous variables, the lag length is chosen based on the SIC criterion and checks are done to ensure the absence of serial correlation.

This model is then used for forecasting. For the iterated approach, annualised quarterly inflation and the markup are the endogenous variables. An approach similar to above was used in the estimation procedure where the estimated model is chosen based on SIC criterion with serial correlation checked. The forecasts are made one period ahead each time, iterated forward for the desired number of periods. Thereafter, the forecasts are summed and brought to annualised terms to generate h-quarters ahead forecasts.

4.0 Results

The comparison of two inflation forecasts is made based on either relative root mean square forecast error, Diebold-Mariano (DM) test or Harvey-Leybourne-Newbold (HLN) test. The relative root mean square error is an appropriate measure of predictive accuracy under quadratic forecast loss function. A number in excess of one indicates forecasting gain in using the previous model if it is measured in the ratio of current forecasts to previous forecasts. The Diebold-Mariano test is a formal finite sample test statistic which compares predictive accuracy taking serial and contemporaneous correlation into consideration. It is the "t-stat" obtained from the regression of x_t on a constant with HAC standard errors, where $x_t = (T_A - T_{F1})_t^2 - (T_A - T_{F2})_t^2$. T_A, T_{F1} and T_{F2} represents actual inflation, inflation forecast from competing model and inflation forecast from alternative model respectively. A rejection of the null hypothesis would mean significant gains using one model compared to the other. However, this test can be over-sized in small samples and is not robust to many periods ahead forecast. The Harvey-Leybourne-Newbold test improves on the former by proposing a size adjustment to the Diebold-Mariano test statistic. Given Diebold-Mariano test statistic t_{dm}, the Harvey-Leybourne-Newbold test statistic is given by $t_{h\ln} = ((n+1-2h+n^{-1}h(h-1))n^{-1})^{0.5} t_{dm}$ where n and h represents the forecast sample size and number of periods ahead respectively.

With these evaluation techniques in mind, this section summarizes the empirical results for forecasts of inflation using single equation models and inflation-markup Model. These forecasts are made one quarter ahead, four quarters ahead and eight quarters ahead for all four nations.

4.1 Evaluation of Single Equation Model Forecasts

The single equation models refer to autoregressive model, bivariate Philips curve model and multivariate models from aggregation of forecasts and information. In general, the autoregressive model provides worse forecast compared to forecast combination or multivariate models. For each country, there is a good mix of predictors that produce better and worse forecast than the autoregressive model and these predictors differ in different forecasting horizon.

4.1.1 Singapore

With reference to Table 3A, in Singapore, for h = 1, the Producer Price Index (PPI) is the best predictor for inflation. This is similar to results in Abeysinghe and Choy (2007) who explains that Singapore's inflation is dependent on import prices, commodity prices and labor costs. In this case, performance of the producer price index, which is an aggregation of these factors mentioned above, lends support to the argument. More importantly, this result finds that transmission of producer to local consumer prices happens very quickly. The next set of important factors is imports and exports. With trade being approximately three times of GDP, Singapore's economic growth, employment and inflation is highly affected by trade. In short, business cycles tend to correlate to trade figures. According to Romer (1993), inflation in an economy tends to depend on the openness of the economy and thus, it is unsurprising that these factors are influential variables when predicting inflation.

For longer forecasting horizons such as h = 4 and 8, the Straits Times Index (STI) and property prices seem to predict inflation well. In fact, the STI outperforms the AR model by more than 20% in both horizons which is substantial as shown in Table 3B. It seems that asset prices, which are forward looking in general, are a good predictor of long term inflation rate in Singapore. The relation between stock prices and inflation in fact goes a long way back. Fischer (1933) claimed that stocks are good hedge against inflation as higher expectation of inflation would lead to higher nominal stock prices. Fama (1981) however disputed the argument claiming that with expected inflation, interest rates are expected to rise thus leading to higher cost of borrowing and fall in stock price due to impending falling profits . Till date, these arguments have been inconclusive. More widely accepted recently is the wealth effect where rising stock prices create illusions about wealth and along with it, assuming consumers are short-sighted, demand for goods rises leading to higher future prices. Thus, in this analysis, this forward looking notion and wealth effect could explain why STI predicts inflation well.

In addition, when forecasting horizon is greater than a year, business variables such as the Composite Leading Index (CLI) and unit business cost are also helpful predictors. The CLI consist of STI, business expectation, oil and non-oil imports and exports amongst many factors and thus predict inflation well due to reasons discussed above. Together with unit business costs, these business surveys are leading indicators and thus predict inflation well.

In general, for Singapore, financial variables such as asset prices and business variables seem to have predictive content whereas money and interest rates related variables do badly in this perspective. For short run forecasting, the producer price index performs best.

4.1.2 Japan

For Japan, as shown in Table 3C, global oil prices and commodity prices predict inflation well in the short-term for h = 1 and 4. Japan is heavily dependent on oil as petroleum is used to generate half of her energy needs. This is best shown in the energy crisis in the 1970s when inflation levels hit a record high due to high oil prices in the gulf. Furthermore, to produce industrial equipments and consumer electronics, large amount of iron ore, copper and bauxite has to be imported since Japan is resource poor in general. Thus, it is well established that global oil prices and commodity prices affect price levels in the Japanese economy especially in the short term. This lends support to Stock and Watson (2003) and LeBlanc and Chinn (2004) who found similar results.

Another useful predictor for one quarter ahead forecast is new machine orders. This indicator is a well known leading indicator of business capital spending and increases are a strong indicator of business confidence and outlook. Thus, this result shows that for non-price domestic variables, new machine orders are helpful in forecasting inflation.

For h = 4 and 8, the dividend yield of stocks seem to predict inflation well. This has been widely studied as the “FED model” in finance. To begin, dividend yields or stock market earning yields are highly correlated to nominal yields on ten year bonds. Polk and Thomson (2006) amongst others found the correlation in developed financial markets such as USA to be 0.8 over the past forty years. Since nominal yields on bonds are anchors to how market participants expect inflation, nominal bond yields move with future inflation, and thus dividend yields help predict longer term inflation. Bekaert and Engstrom (2010) extends this idea by applying modern asset pricing theory incorporating uncertainty and habit-based risk aversion in a framework explaining equity yields and future inflation. Hence, dividend yield is a valuable leading indicator and is thus helpful in predicting inflation well-established financial markets in Japan. The result extends to Hong Kong as well.

One predictor that seems to also possess predictive content across all horizons is the nominal effective exchange rate (NEER). This is possibly due to one of the objectives of the central bank which is to adjust the Yen to bring about higher economic growth via export competitiveness. This result, similar to Ito and Sato (2006) in their VAR analysis, shows that exchange rate adjustments does have an impact on price stability.

To conclude, with reference to Table 3D, global commodity prices and dividend yield are useful predictors of inflation in the short and long term respectively. The former outperforms the autoregressive model by 10% while the latter by more than 15%. Monetary variables and trade variables seem to however possess poor predictive content.

4.1.3 South Korea

For South Korea, unemployment and business indices predicts inflation well across all time periods. Business index is a leading indicator that surveys future expectation of business profits and economic growth. Moreover, research by the Korean Central Bank shows that the survey is meant to reflect one year ahead business activity. Thus, it is unsurprising that it helps to predict inflation well. For unemployment, a reason for its predictive content is due to the structure of the economy. In general, the South Korean economy is export-oriented and is driven by sales of semi-conductors, telecommunication devices, automobiles, petrochemical products and ships. These industries, comprising big conglomerates such as Samsung, Hyundai, Posco and LG, produce the bulk of exports which require large amount of manpower. Thus, with every global economic upturn, due to expectation of higher prices from increasing demand, more workers are required in the production process. Hence, unemployment in the classical Phillips curve setting helps predict inflation well in South Korea

Another variable that outperformed the AR model consistently in all horizons is the discount rate. The Korean Central Bank (KCB) adjusts the base rate every month in consideration of price movements and economic growth. Using policy instruments, the discount rate converges to the base rate and affects interest rates which influences investment and consumption decisions. Thus, discount rate is useful in forecasting future inflation. This result lends support to the policy actions of KCB.

In general, it is evident that the business index, unemployment rate and the discount rate helps to predict inflation in South Korea across all horizons. These gains in forecasting are more than 20% as shown in Table 3F when compared to autoregressive model. Two other factors that could be useful as seen in Table 3F are property prices in the short run and dividend yield in the long run. Monetary variables once again perform poorly in comparison. Hence, these results show that business and labor variables tend to be useful predictors of inflation for heavily-industrialised economies like South Korea.

4.1.4 Hong Kong

In Hong Kong, property prices are the most important predictor in short term inflation forecasting as they outperform forecasts from the autoregressive model by 10% to 15%. This is shown in Table 3H and is similar to reports from many international banks that use housing prices as an anchor of short term inflation expectation. This is because of the high weights given to property rents and prices in computing the CPI. Chiu (2003) depicts this best showing that property prices lead inflation be it when it is positive or negative. This result lends support to recent government policy aimed at curbing rising property prices which has its spill-over effects in terms of higher cost of living. Along with housing prices, business construction output also predicts inflation well as it indicates demand for housing thus making it another predictor of future inflation.

For longer forecasting horizon such as h = 4 and 8, dividend yield also seem to predict inflation. Being a financial centre with an active bond market, similar to previous argument, dividend yields proxy nominal bond yields which represent inflation expectation. Another financial variable that is important in Hong Kong is also the market capitalisation of the Hong Kong Stock Exchange (HKSE). With higher expected inflation, investors expect nominal share prices to rise in tandem thus leading to higher stock prices which generate higher market capitalisation of firms in the stock exchange. Further, this is compounded by the fact that more firms list on stock exchanges during periods of business optimism which precedes higher inflation.

In general, as shown in Table 3H, property related variables seem to have the greatest predictive content for forecasting inflation in Hong Kong. This result suggests that in order to rein in price stability, it is important to control housing prices and that the Hong Kong Monetary Authority could in fact use this predictor to anchor inflation expectations.

4.2 Evaluation of VAR Inflation-Markup Model Forecasts

Before proceeding to the results of the forecast comparison, it is worth noting that, for the inflation-markup model, as depicted in Figure 2A to 2D, a strong negative relation is found in Japan and South Korea. This result is similar to Sekine (2001). However, for Singapore, a positive relation holds meaning that prices and markup moves in tandem. This means that firms, in general, had been able to pass on rising costs to consumers. For Hong Kong, the relationship is very weak, suggesting that the inflation-markup model may not help to forecast inflation well, which is indeed the case as discussed later.

In the comparison of inflation forecasts between the inflation-markup model and SEMs, two related methods are reported. The first is the relative root mean square error (RRMSE) where the inflation-markup model is taken as baseline. More formally, forecasts are also compared using the Diebold-Mariano test and Harvey-Leybourne-Newbold test.

As seen in Table 4A, the first column represents the country and the forecasting horizon. For example, SG4 means forecasting Singapore's inflation four quarters ahead. The fourth and fifth column represents the RRMSE of the aggregate forecasting model and aggregate information model, whose compositions are found in Table 4B. The root mean square error of the inflation-markup model using the iterative method has been scaled to one and the other models use this as a reference. It is evident that the inflation-markup model using iterated method outperforms the autoregressive model across countries and horizons with outperformance improving as forecast horizon increases. This is because of the additional markup variable which helps to predict inflation. However, the best single equation model, be it from the aggregation of forecast or aggregation of information, outperforms the inflation-markup model in most circumstances except for forecasting inflation eight quarters ahead in Singapore, Japan and South Korea. Thus, one conclusion from the result is that the inflation-markup model performs better as forecasting horizon increases. This result holds even when the direct forecasting method, as described previously in Section 3.3, is used for the inflation-markup model.

Using formal tests such as the Diebold-Mariano tests and Harvey-Leybourne-Newbold tests, the results become less clear cut. The null hypothesis of these tests is that the forecasting ability of the inflation-markup model provides a better forecast than the competing model. A rejection of the null at 5% or 10% confidence level would imply a p-value of less than 0.05 and 0.10 respectively in the second, third and fourth column of Table 4C and 4D.

As seen in Table 4C, the forecasting gains using the inflation-markup model on those SEMs that it outperformed is insignificant at even 10% significance level using Diebold-Mariano test. On the other hand, forecasts from the aggregate information model provide significant gains on the inflation-markup model for one quarter ahead inflation in Singapore and South Korea. However, correcting for small sample size and number of periods ahead, the Harvey-Leybourne-Newbold test as seen in Table 4D, shows that forecast from the inflation-markup model for eight quarters ahead inflation in South Korea and Japan outperforms the single equation models' forecasts significantly. Moreover, the inflation-markup model shows superiority in forecasting inflation one year and two year ahead when compared to the autoregressive model.

To summarise, the inflation-markup model does improve on the SEMs especially when forecasting horizon increases. These gains are found to be significant for South Korea and Japan at longer horizons. For Hong Kong, the inflation-markup forecasts fared poorly.

5.0 Robustness Check

This section examines the robustness of the results mentioned above. Structural breaks or instabilities have been a widely accepted source of forecasting failure in macroeconomics. Research by Pesaran and Timmermann (2004), Pesaran and Pettenuzzo (2006) and Koop and Potter (2007) amongst many have found instabilities to be costly as it affects the stability of forecasting results.

As mentioned previously in Section 2.2, inflation had been different in all four countries for reasons such as changing structure of the economy and differences in monetary operatives amongst central banks. In South Korea, inflation targeting became the main objective of the KCB only in the 1990s. This is clearly shown as inflation was much higher and more volatile in earlier years and thus could be a reason for structural changes in our inflation modelling. Further, the differences in the state of the economy could have also affected inflation modelling in Japan as they suffered a long recession after the crash of stock markets. In Hong Kong, the re-integration into China has also led to re-adjustments in terms of prices of output and wages. This could possibly also lead to changes in the state of economy and would have been an important cause of structural break in modelling inflation. **Many solutions have been put forth in order to circumvent these issues of structural change, depending on the size of break, distance of break and correlation between real and forecasted values.** If break dates are known, including data prior to the break date could induce gains in forecasting. Pesaran and Timmermann (1999) assumed the availability of break dates and created an optimal window forecasting scheme to minimise root mean square error. Upon further research, Pesaran and Timmermann (2004) found that applying either recursive or rolling window could help to mitigate some of the bias. The recursive or expanding window allows new data to enter into the analysis upon release while the rolling window fixes an optimal window size whose date of estimation changes in every analysis. These are the most widely applied methods and are therefore applied in this paper as a robustness check.

When time and size of break is uncertain, Pesaran and Pick (2011) showed that the averaging forecast across windows works best. However, these methods proved to be overly-cumbersome. Pesaran and Pick (2011) afterwhich introduced discrete and continuous weighting schemes that minimises root mean square error without locating the size and time of structural break. These weights generate forecast which consistently outperforms the autoregressive model in Monte Carlo simulation. Thus, these structural break robust forecasts (SBRF) also help to check on the robustness of results in this paper.

5.1 Expanding Window Forecasts

Previously, we estimated the forecasting models over an initial sample period and forecasted over the forecast period without re-estimation. Now, we consider expanding the estimation sample new data is obtained. The expanding window forecasts are generated at each quarter appending previous data-set with an additional data point as new survey data enters. Pesaran and Timmermann (2004) found that for a small structural break, expanding window is suitable as firstly, it allows estimated coefficients in models to vary slightly thus mitigating bias at each point in time and secondly, it captures all available information. In this analysis, the expanding window method first estimates the model from 1978Q1 to 2001Q4 and forecasts inflation for 2002Q1. When data for predictors in 2002Q1 is collected, estimation is now made from 1978Q1 to 2002Q1 for inflation forecast in 2002Q2. This is done until the series of inflation forecasts from 2002 to 2010 is collected. Thus, this more closely resembles a real-time forecasting simulation. The RMSE is also computed similar to methods discussed above. The estimation procedure remains unchanged where the best model, in terms of lowest SIC, is chosen recursively after applying four lags for each regressor. In doing so, each model may differ in the number of lags it contains in different time periods. After which, each model chosen is used for forecasting.

5.2 Structural Break Robust Forecasts

More recently, Pesaran and Pick (2011) suggested a weighting scheme that produces forecasts that outperformed models estimated by un-weighted Ordinary-Least-Squares (OLS) estimation, where each data point carries the same weight. These weights are generated assuming that there exist structural breaks in the data generating process and the forecasts are referred to as structural break robust forecast. Using two of the methods described above, results show that predictors that contain informational content for forecasting inflation in general remains unchanged.

As with many methods applied to circumvent the issue of structural break, the time of break and size of break are influential decisions that would affect forecasting results. In the previous section, the expanding window method is advocated only if size of break is small while other methods such as applying the pre-break window method depends on the time of break. However, these factors are difficult to estimate in general. Therefore, Pesaran and Pick (2011) developed weights that are robust to size and time of break. For a large sample, the weights are given by:

$$w_t^* = \frac{-\log(1 - t/T)}{T - 1} \tag{12}$$

$$w_T^* = \frac{\log(T)}{T - 1} \tag{13}$$

where w_t^* is the weight for t=1, 2,...., T-1 where t represents the period the data is in and T represents the estimation sample size. Due to discretization, the weights do not sum to infinity and hence is scaled back to proportion where:

$$w_t = \frac{w_t^*}{\sum_{s=1}^{T} w_s^*} \tag{15}$$

More details of this approach and properties is found in Pesaran and Pick (2011). In our application, the estimation and forecasting period remains unchanged from 1978 to 2001 and 2002 to 2010 respectively and the best model is once again chosen recursively up to four lags via the SIC criterion for forecasting purposes.

5.3 Robustness of Results

In general, both the expanding window and structural break robust forecast support the previous results. Predictors that do well in forecasting inflation in each country during different time period continue to do so as shown in Table 5A to 5L. However, slight changes in position are inevitable as differences in RMSE between predictors are relatively small.

For Singapore, using the expanding window method, variables such as PPI, imports, exports continue to do well for h = 1 while the STI continues outperform other predictors for h = 4 and 8. This results hold even when using structural break robust method. For Japan, similar to results mentioned in Section 4.1.2, commodity prices continue to be useful predictors for h = 1 while dividend yield, discount rate and NEER continue to perform well for h = 4 and 8. In this case, the expanding window method lends greater support as compared to structural break forecast method as the former produces results closer to the estimation and forecasting procedure in Section 3.

For South Korea, business index and unemployment continue to be the most important predictors in forecasting inflation as supported by the expanding window method. Other predictors such as discount rate and property prices that did well previously also continue to do so. For Hong Kong, property prices are still the most important predictor for inflation using both methods and that business construction output continues to predict inflation well as forecasting horizon increases.

In summary, these results suggest that predictors as mentioned in Section 4 are robust to structural breaks as different methods applied to mitigate the issue lends support to the initial results.

6.0 Discussion and Conclusion

This paper is the first systematic analysis of inflation forecasting in Asian countries such as Singapore, Japan, South Korea and Hong Kong. Predictors from business activities, financial activities, trade activities, labour markets, interest rate markets, money markets, exchange rate markets and global commodity markets were analysed for marginal predictive content in forecasting inflation one quarter, four quarters and eight quarters ahead. The best forecasts were then combined by either pooling of forecasts or pooling of information and evaluated against forecasts from the inflation-markup model. Robustness checks via expanding window method or structural break robust forecasting method were also conducted to ensure results are relevant in the presence of structural breaks. A few important conclusions were made.

First, for open economies with a developed financial sector which allows easy movement of capital, asset prices produce the best inflation forecast. This is evident in Singapore and Hong Kong where financial variables such property prices, stock indexes and market capitalisation produces the best forecast. For heavily-industrialised nations like South Korea, due to the volume of manpower needed in production, inflation is best predicted by unemployment. For resource poor nations such as Singapore and Japan, it is evident that short term inflation is best predicted by price variables such as PPI, import price, oil price and global commodity price. This lends support to these governments' decision of currency appreciation to mitigate imported inflation. More interestingly, dividend yield seems to be a predictor that is robust to forecasting horizons in most economies except Singapore. This result, which is also captured in empirical finance, is important for central banks as it reflects how financial market participants may anchor their inflation expectations. To conclude, this analysis have shown that applying the modified Stock and Watson Philips curve using correctly chosen predictors could in fact be helpful in forecasting inflation compared to the atheoretical autoregressive model.

Second, the inflation-markup model does perform better in forecasting inflation compared to SEMs as forecasting horizon increases. This result, first confirmed using the iterated approach, is robust even when using the direct approach. Evidently, for Hong Kong, where the inflation-markup model performs poorly, inflation forecasts were worse than SEMs whereas for Japan and South Korea, where the negative relationship is strong, the inflation-markup model forecasts better than SEMs. This result holds when tested formally using the Harvey-Leybourne-Newbold test and could thus become an important inflation forecasting model for central banks in Asia.

Third, our results are in general robust to structural breaks. With close to one hundred observations used in the analysis, structural breaks or model instability may result. However, stability diagnostics done graphically using recursive estimates showed coefficients to be largely stable. More importantly, this paper carries out formal methodologies to circumvent the issue by applying the expanding window forecasts and structural break robust forecasts. Results from these forecasts showed that predictors that did well previously continued to do well.

However, a few improvements could still be made to better results above. First, it is important to note that the framework applied in this paper is of linear modelling. If the relation between inflation and some of the predictors is nonlinear, forecasting improvements could be obtained making forecasts more informative for central banks. Hence, nonlinear forecasting could complement this analysis. Second, for the inflation-markup model, a better model could be estimated for forecasting purposes if more data was available. Due to the setup of the VAR, adding more predictors or more lags of predictors in the regression will reduce the degrees of freedom rapidly thus creating problems in estimation. In this case, techniques such as Bayesian estimation could be applied to encompass more prior information and judgement about inflation. Results from the Bayesian VAR forecasting could be used to compliment results from in our inflation-markup model analysis.

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APPENDIX

Figure 1: Annualised Quarterly Inflation Rate for Four Asian Economies

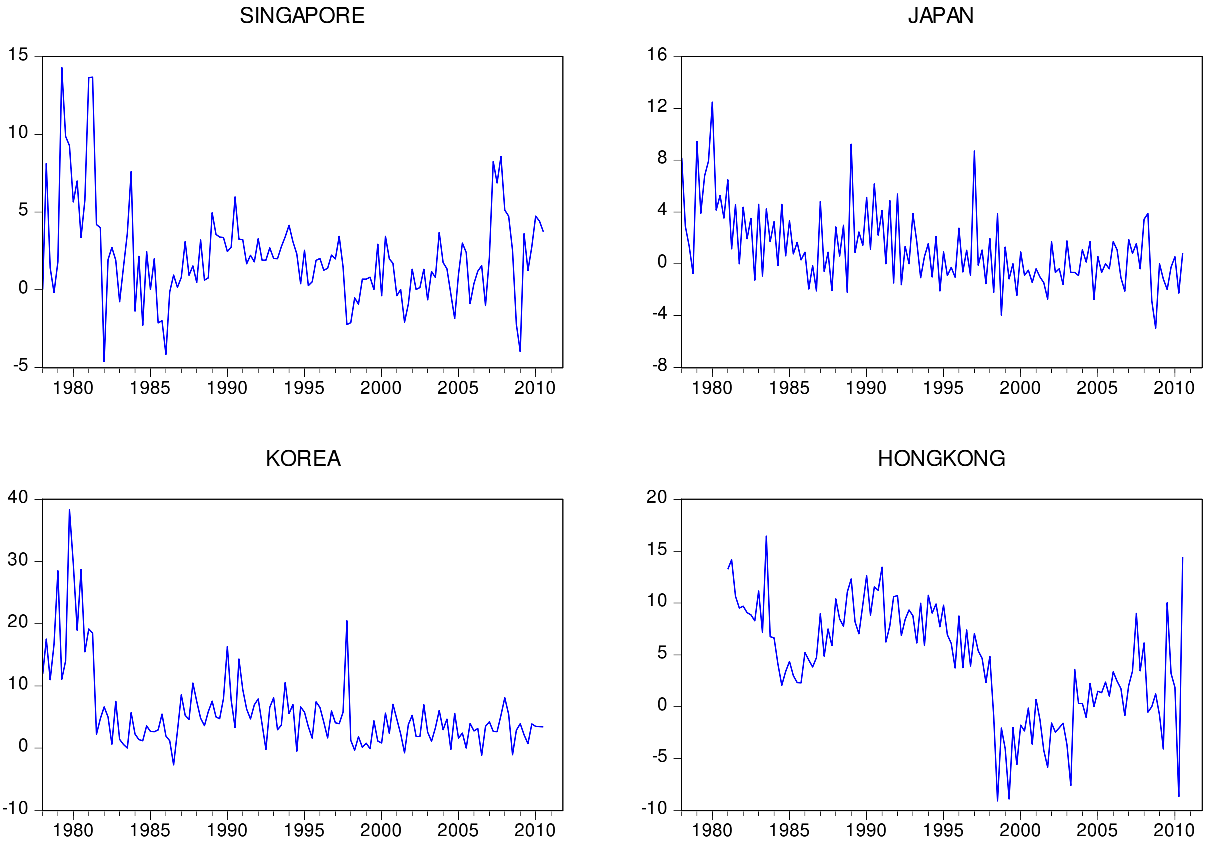

Table 1: Summary Statistics of Inflation Rates of Four Asian Economies

	Singapore	Japan	Korea	Hong Kong
Mean	2.14	1.19	5.81	4.40
Standard Deviation	3.14	2.92	6.43	5.46

Table 2: List of Predictors for Each Country

Singapore	Japan	South Korea	Hong Kong
b_buisness expect.	b_consumer con. ind.	b_business index	b_construction out.
b_composite lead.	b_industrial prod.	b_electricity	b_industrial prod.
f_market capital.	b_investment climate	b_industrial prod.	b_retail sales
f_straits times index	b_new machine ord.	b_shiping index	f_deposit rate

h_property prices	b_s.m.e. sales	f_bond prices	f_dividend yield
i_deposit rates	f_credit card spend.	f_dividend yield	f_hang seng ind.
i_discount rates	f_dividend yield	f_korean stock ind.	f_market capital.
i_lending rates	f_int.rate. spread	f_market capital.	f_usd ex. rate
i_norm. eff. ex. rate	f_market capital.	h_housing prices	h_property px. off.
i_real eff ex. rate	f_tokyo stock index	i_deposit rate	h_property px. Res.
l_productivity	h_housing starts	i_discount rate	i_discout rate
l_unemployment	i_bond price	i_money market rate.	i_foreign exchange
m_money circulation	i_discount rate	i_norm. eff. ex. rate.	i_lending rate
m_domestic credit	i_foreign exchange	l_emploment manu.	i_money mark. rate
m_foreign reserves	i_interbank 3month	l_unemployment	i_norm. eff. ex. rate
m_m1	i_money mark. rate	m_domestic credit	l_unemployment
m_m2	i_norm. eff. ex. rate	m_financial asset	m_banking asset
m_m3	i_real eff. ex. rate	m_m1	m_money circulation
m_quasi money	i_treasury bill	m_m2	m_m1
markup	m_m1	m_quasi money	m_m2
p_exp. price index	m_m2	markup	m_m3
p_imp. price index	m_m3	p_sk commod. price	m_time deposit rate
p_prod. price index	m_country reserves	p_exp. price index	markup
p_manufact. cost	markup	p_imp. price index	p_prod. price index
p_unit labor cost	p_jap commod. price	p_prod. price index	p_unit labor cost
t_capital acct.	p_exp. price index	p_unit labor cost	t_export
t_exports	p_imp. price index	p_wage manu.	t_export value
t_export vol.	p_prod. price index	t_current acct.	t_import
t_financial acct.	p_unit labor cost	t_export	t_import value
t_import	t_export	t_export vol.	t_import vol.

t_import vol.	t_export vol.	t_financial account.	u_discount rate
u_discount rate	t_import	t_import	u_money supply
u_money supply	t_import vol.	t_import vol.	v_stock price
v_stock price	u_discount rate	u_discount rate	v_commodity price
v_commodity price	u_money supply	u_money supply	v_oil price
v_oil price	v_stock price	v_stock price	
	v_commodity price	v_commodity price	
	v_oil price	v_oil price	

Note: All small letters represent different categories of predictors. 'b' represents business, 'f' represents financial, 'h' represents housing, 'i' represent interest rate, 'l' represents labor, 'm' represents monetary, 'p' represents price, 't' represents trade, 'u' represents USA and 'v' represent global commodity variables.

Table 3A: Top 8 Predictors in Singapore for H= 1, 4, 8

Position/Horizon	H=1	H=4	H=8
1st	Producer Price Index	STI	STI
2nd	Imports	Compo Lead Index	Domestic Credit
3rd	STI	Property Price	Property Price
4th	Exports	DJIA	Unit Biz Cost
5th	Market Cap.	Unit Biz Cost	Market Cap.
6th	DJIA	Real Eff. Ex. Rate	Commodity Price
7th	Import Price	Export Vol.	Composite leading
8th	Property Price	Producer Price Index	Unemployment

Table 3B: Predictors in Singapore Outperforming AR Model

(No Chronological Order)

% Gains From AR	H=1	H=4	H=8
By >20%		STI	STI
By >15%	Producer Price Index	Compo Lead Index	Domestic Credit
		Property Price	Property Price
			Unit Biz Cost
By >10%	Imports	DJIA	Market Cap.

	STI		Commodity Price
	Exports		Composite leading
	Market Cap.		Unemployment

Table 3C: Top 8 Predictors in Japan for H= 1, 4, 8

Position/Horizon	H=1	H=4	H=8
1st	Oil	Dividend Yield	Dividend Yield
2nd	Producer Price Index	Oil	Market Cap
3rd	Import Price Index	Commod. Price	Consumer Confid.
4th	JP Commod. Price	Jap Discount Rate	Discount rate
5th	New Machine	Norm. Eff. Ex. Rate	Unit Labor Cost
6th	Import	Consumer Confid.	Norm. Eff. Ex. Rate
7th	Norm. Eff. Ex. Rate	Discount rate	Commodity Price
8th	DJIA	MM rate	Producer Price Ind.

Table 3D: Predictors in Japan Outperforming AR Model

(No Chronological Order)

	H=1	H=4	H=8
By >15%	Oil		Dividend Yield
			Market Cap
			Consumer Confid.
By >10%	Producer Price Index	Dividend Yield	Discount rate
	Import Price Index	Oil	Unit Labor Cost
	JP Commod. Price	Commod. Price	Norm. Eff. Ex. Rate
		Jap Discount Rate	Commodity Price
		Norm. Eff. Ex. Rate	Producer Price Ind.
			Interest Spread
			Real Eff. Ex. Rate

Table 3E: Top 8 Predictors in Korea for H= 1, 4, 8

Position/Horizon	H=1	H=4	H=8
1st	Unemployment	Business Index	Unemployment
2nd	Business Index	Unemployment	Dividend Yield
3rd	Property Price	Property Price	Business Index
4th	Discount Rate	Dividend Yield	Discount rate
5th	Oil	Market Capital.	Markup
6th	Commod. Price	Discount Rate	Oil
7th	Dividend Yield	Markup	Unit Labor Cost
8th	Markup	Unit Labor Cost	Market Capital.

Table 3F: Predictors in Korea Outperforming AR Model

(No Chronological Order)

	H=1	H=4	H=8
By >20%	Unemployment	Business Index	Unemployment
	Business Index	Unemployment	Dividend Yield
	Property Price		Business Index
	Discount Rate		Discount rate
			Markup
			Oil
			Unit Labor Cost
			Market Capital.
			Commod. Price
			Producer Price Index
By >15%	Oil	Property Price	
		Dividend Yield	
		Market Capital.	
By >10%	Commod. Price	Discount Rate	Property Price
	Dividend Yield	Markup	
	Markup	Unit Labor Cost	
	Industrial Prod.	KSI	
	Market Capital.		
	Export Vol.		

Table 3G: Top 8 Predictors in Hong Kong for H= 1, 4, 8

Position/Horizon	H=1	H=4	H=8
1st	Property Office	Property Res	Biz Con Output
2nd	Oil	Property Office	MM Rate
3rd	Biz Con Output	Dividend Yield	Dividend Yield
4th	Market Capital.	Market Capital.	Property Res
5th	Property Res	MM Rate	Market Capital.
6th	Bank Asset	HKSI	Production Index
7th	M1	Foreign Ex.	US Money Supply
8th	M2	DJIA	US Discount Rate

Table 3H: Predictors in Hong Kong Outperforming AR Model

(No Chronological Order)

	H=1	H=4	H=8
By >10%	Property Office	Property Res	Biz Con Output
	Oil		
	Biz Con Output		

Figure 2A: Scatter Plot Relationship of Inflation Markup in Singapore

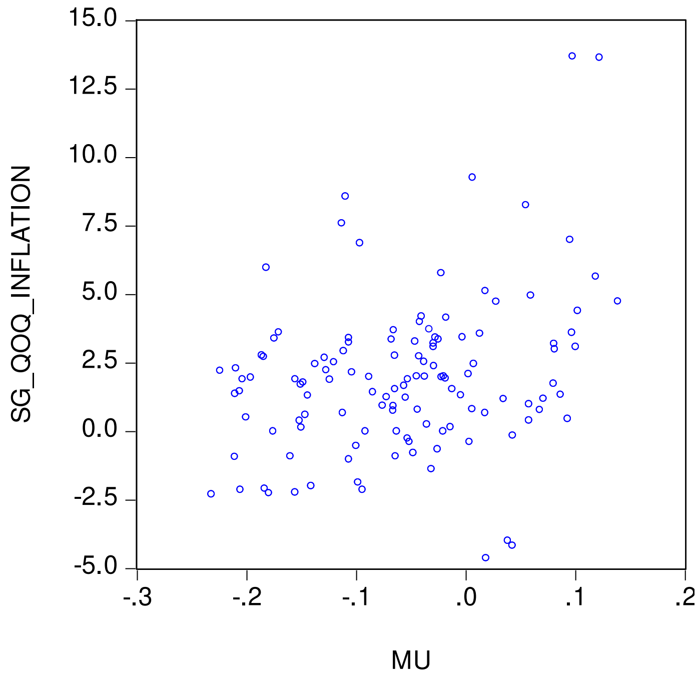

Figure 2B: Scatter Plot Relationship of Inflation Markup in Japan

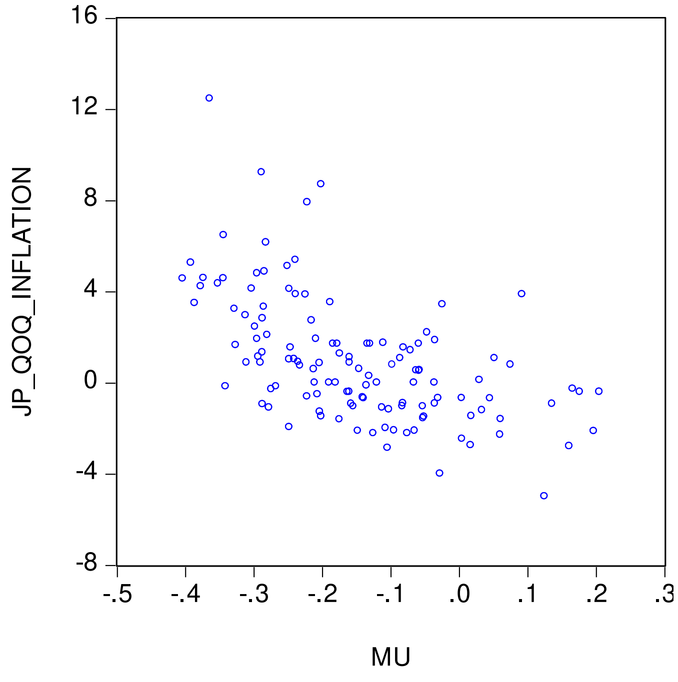

Figure 2C: Scatter Plot Relationship of Inflation Markup in Korea

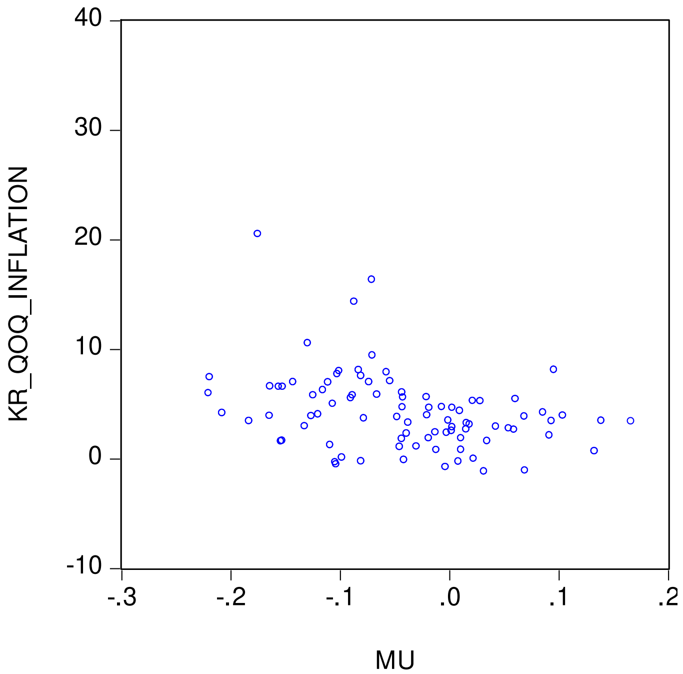

Figure 2D: Scatter Plot Relationship of Inflation Markup in Hong Kong

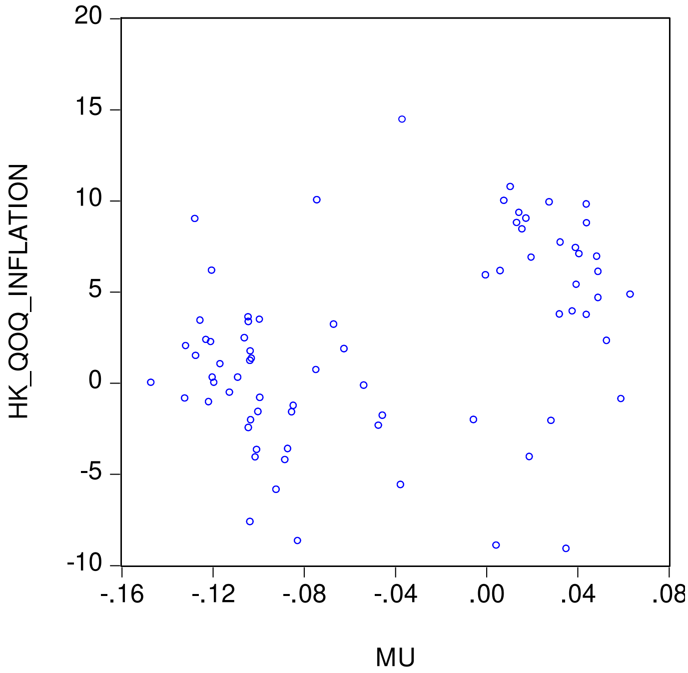

Table 4A: Relative Root Mean Square Forecast Errors (RRSME)

(Bold implies Inflation-Markup (MU) gains on best Single Equation Models (SEMs))

Country/RRSME	MU-Iterated	AR	AF	AI
SG1	1	1.01648	0.83362	0.74828
SG4	1	1.38784	0.89738	0.89738
SG8	1	1.89957	**1.28618**	**1.29103**
JP1	1	1.0651	0.80275	0.86903
JP4	1	1.32856	**1.12642**	**1.09539**
JP8	1	1.69176	**1.27269**	**1.14477**
KR1	1	1.11746	0.83403	0.83445
KR4	1	1.3107	0.93608	0.949
KR8	1	2.2549	**1.27304**	**1.27304**
HK1	1	1.06244	0.86923	0.86923
HK4	1	1.02126	0.91717	0.86998
HK8	1	1.26877	0.99465	0.99465

Table 4B: Composition of Aggregate Forecast and Aggregate Information Models

Country	Aggregate Forecast	Aggregate Information
SG1	PPI, Import, STI	STI
SG4	STI	STI
SG8	STI, Domestic Credit	PPI, Import, STI, Export, Mar. Cap.
JP1	Oil Px., PPI, Import Px., New Mach.	Oil Px.
JP4	Div. Yield, Oil Px., Commod Px.	Div Yield, Oil Px., Jap Dis. Rate.
JP8	Div. Yield, Mar. Cap., Con. Conf., ULC	Div. Yield, Mar. Cap., Con. Conf.
KR1	Unemployment, Prop. Px.	Unemployment
KR4	Business Index, Prop. Px.	Business Index
KR8	Unemployment	Unemployment
HK1	Prop. Px. Office	Prop Px. Office
HK4	Prop. Px Resid.	Prop. Px Resid., Mar. Cap.
HK8	Business Con. Output	Business Con. Output

Table 4C: P-Value for Diebold Mariano Test

(* denote significance at 10% while ** means 5%, bold implies MU gains on others)

Country/DM	AR	AF	AI
SG1	0.7191	0.1092	0.0474**
SG4	0.139	0.3397	0.3397
SG8	0.0756*	**0.4305**	**0.4046**
JP1	0.1107	0.1869	0.1227
JP4	0.1975	**0.4912**	**0.7914**
JP8	0.005*	**0.1407**	**0.6074**
KR1	0.2256	0.0134**	0.0181**
KR4	0.0261**	0.5452	0.6229
KR8	0.0106**	**0.2478**	**0.2478**
HK1	0.2422	0.1627	0.1627
HK4	0.1613	0.5739	0.9398
HK8	0.203	0.9796	0.9796

Table 4D: P-Value for Harvey Leybourne Newbold Test

(* denote significance at 10% while ** means 5%, bold implies MU gains on others)

Country/DM	AR	AF	AI
SG1	0.357596	0.052174*	0.022232**
SG4	0.04914**	0.142274	0.142274
SG8	0.008884**	**0.141905**	**0.128757**
JP1	0.052872*	0.090337*	0.057594*
JP4	0.074637*	**0.219952**	**0.383107**
JP8	0.000139**	**0.023896****	**0.241816**
KR1	0.109514	0.006111**	0.008327**
KR4	0.006681**	0.248608	0.290474
KR8	0.000427**	**0.059078***	**0.059078***
HK1	0.117765	0.078387*	0.078387*
HK4	0.058619*	0.264006	0.466226
HK8	0.042938**	0.486038	0.486038

Table 5A: Robustness of Results in Singapore for H = 1

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Producer Price Index	2	0.72	4	0.75
2nd	Imports	1	0.82	1	0.66
3rd	STI	4	0.77	2	0.71
4th	Exports	N.P.	0.83	3	0.73
5th	Market Cap.	6	0.81	6	0.81

Table 5B: Robustness of Results in Singapore for H = 4

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	STI	1	0.49	1	0.49
2nd	Compo Lead Index	4	0.70	3	0.67
3rd	Property Price	3	0.70	4	0.72
4th	DJIA	2	0.69	6	0.83
5th	Unit Biz Cost	8	0.94	5	0.80

Table 5C: Robustness of Results in Singapore for H = 8

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	STI	1	0.52	1	0.61
2nd	Domestic Credit	2	0.66	N.P.	1.00
3rd	Property Price	3	0.66	3	0.73
4th	Unit Biz Cost	6	0.76	2	0.64
5th	Market Cap.	4	0.75	5	0.76

Table 5D: Robustness of Results in Japan for H = 1

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Oil	1	0.67	1	0.51
2nd	Producer Price Index	4	0.76	2	0.66

3rd	Import Price Index	5	0.77	N.P.	0.91
4th	JP Commod. Price	2	0.71	N.P.	1.00
5th	New Machine	6	0.86	3	0.76

Table 5E: Robustness of Results in Japan for H = 4

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Dividend Yield	N.P.	0.87	5	0.83
2nd	Oil	8	0.86	N.P.	0.85
3rd	Commod. Price	3	0.83	4	0.82
4th	Jap Discount Rate	1	0.82	N.P.	0.95
5th	Norm. Eff. Ex. Rate	4	0.83	N.P.	0.86

Table 5F: Robustness of Results in Japan for H = 8

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Dividend Yield	2	0.73	5	0.78
2nd	Market Cap	3	0.73	N.P.	0.89
3rd	Consumer Confid.	1	0.70	1	0.58
4th	Discount rate	4	0.74	N.P.	1.03
5th	Unit Labor Cost	5	0.77	3	0.75

Table 5G: Robustness of Results in Korea for H = 1

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Unemployment	1	0.55	1	0.81
2nd	Business Index	2	0.58	5	0.91
3rd	Property Price	3	0.60	6	0.95
4th	Discount Rate	4	0.64	N.P.	1.00
5th	Oil	8	0.71	N.P.	1.14

Table 5H: Robustness of Results in Korea for H = 4

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Business Index	1	0.54	N.P.	1.10
2nd	Unemployment	2	0.58	6	0.91
3rd	Property Price	3	0.65	N.P.	1.14
4th	Dividend Yield	5	0.68	N.P.	1.81
5th	Market Capital.	6	0.75	N.P.	1.67

Table 5I: Robustness of Results in Korea for H = 8

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Unemployment	1	0.35	2	0.65
2nd	Dividend Yield	3	0.45	N.P.	1.31
3rd	Business Index	2	0.45	5	0.78
4th	Discount rate	5	0.47	N.P.	1.06
5th	Markup	6	0.54	N.P.	1.03

Table 5J: Robustness of Results in Hong Kong for H = 1

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Property Office	1	0.69	1	0.87
2nd	Oil	6	0.82	N.P.	1.25
3rd	Biz Con Output	N.P.	0.91	3	0.92
4th	Market Capital.	8	0.83	N.P.	1.05
5th	Property Res	3	0.76	2	0.88

Table 5K: Robustness of Results in Hong Kong for H = 4

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Property Res	2	0.84	4	0.92
2nd	Property Office	5	0.95	N.P.	1.09
3rd	Dividend Yield	4	0.89	7	0.97
4th	Market Capital.	1	0.82	N.P.	1.17
5th	MM Rate	N.P.	1.00	2	0.89

Table 5L: Robustness of Results in Hong Kong for H = 8

Position	Variable	EWF Pos.	RMSE	SBRF Pos.	RMSE
1st	Biz Con Output	1	0.70	1	0.61
2nd	MM Rate	N.P.	1.23	3	0.74
3rd	Dividend Yield	4	0.91	8	0.99
4th	Property Res	3	0.88	N.P.	1.01
5th	Market Capital.	2	0.83	4	0.95

Note: N.P. means not in top 8 within selection while RMSE is relative to each procedures' own AR model's root mean square forecast errors.
