

# Forecasting in a Small Open Economy: Evidence from Hong Kong

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## 1 Motivation

The main text studies forecasting performance in the United States, a large and relatively closed economy with long and stable macroeconomic series, which is a good setting for both Bayesian VARs and factor models. Therefore, we want to explore whether the same results will be replicated in an economy that is smaller, more open, and more exposed to external shocks.

Hong Kong provides exactly this setting. Its macro data are noisier, the available sample is shorter, and the dimensionality of the dataset is higher. If similar tendencies still appear—short-run strength of BVARs, smoother long-run performance of factor models, and increasing similarity across methods as the forecast horizon expands—they are likely to be common properties of the models rather than features specific to a large economy.

## 2 Data and Models

The dataset contains 105 quarterly observations on 63 macroeconomic and financial series from 1999Q3 to 2025Q2.<sup>1</sup> The variables cover real activity, prices, interest rates, credit, housing markets, and external series from the United States and Mainland China, as Hong Kong operates under a currency board with a free financial market and thus it is heavily influenced by external shocks. All series are transformed to achieve approximate stationarity.

We analyze forecasting models of different sizes for three target macroeconomic variables: real GDP, consumption, and employment. This setup parallels the main paper but places the models under stronger pressure because of Hong Kong’s shorter sample, higher noise, and higher dimensional setting. Therefore, we consider five models as follows.

(i) **VAR**, a classical VAR estimated on the 3 target variables, with the lag length selected by BIC, viewed as benchmark due to approximate stationary data.

(ii) **LBVAR**, a large-scale BVAR estimated on all 63 variables, using a Minnesota-type prior and empirical Bayes grid search to determine the hyperparameter.

(iii) **SBVAR**, a small-scale BVAR estimated on 13 variables selected by LASSO and a grid search with recursive validation. Using this reduced subset to estimate a BVAR allows us to test whether combining variable selection with shrinkage is helpful in this setting.

(iv) **DFM**, a dynamic factor model estimated on all 63 variable, with factors selected by ICp2 and estimated via EM and Kalman filter–smoother.

(v) **FAVAR**: a factor-augmented VAR estimated on 6 variables, combining the extracted factors selected in DFM with the three target variables, allowing us to test whether adding common factors improves forecasts in our setting.

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<sup>1</sup>All data are obtained from the websites of the Census and Statistics Department of Hong Kong, the Rating and Valuation Department of Hong Kong, The Land Registry of Hong Kong, Hong Kong Monetary Authority, National Bureau of Statistics of China, Federal Reserve Bank of St. Louis. Detailed description of data is provided in the attached folder.

All models are evaluated in a recursive out-of-sample root mean squared errors (RMSE). The initial estimation window is ( $T_0 = 30$ ) quarters, after which the sample expands one quarter at a time to generate forecasts from one to eight quarters ahead ( $h = 1-8$ ).

### 3 Results and Implications

Table reports the RMSEs of all models. We find that across all three target variables, the overall results is consistent with the empirical part in the main text: the overall pattern is consistent with the empirical results in the main text: BVAR-type models perform relatively well at short horizons, while factor-based approaches become more competitive at long horizons, and they convergence as the horizon expands.

Table 1: Root Mean Squared Error Across Models and Forecast Horizons

| Target / Model  | h=1    | h=2    | h=3    | h=4    | h=5    | h=6    | h=7    | h=8    |
|-----------------|--------|--------|--------|--------|--------|--------|--------|--------|
| <b>(A) GDP</b>  |        |        |        |        |        |        |        |        |
| VAR             | 1.8124 | 1.7468 | 1.7774 | 1.7768 | 1.7605 | 1.7637 | 1.7349 | 1.7159 |
| LBVAR           | 2.3121 | 2.1061 | 1.9619 | 2.5945 | 2.5228 | 2.1839 | 2.9580 | 4.9285 |
| SBVAR           | 2.0481 | 1.9088 | 1.9731 | 2.0385 | 2.0468 | 2.1373 | 2.1548 | 2.2464 |
| DFM             | 1.8532 | 1.8447 | 1.9038 | 1.8810 | 1.8774 | 1.8845 | 1.8263 | 1.8490 |
| FAVAR           | 1.9527 | 1.9235 | 1.8374 | 1.8437 | 1.7944 | 1.7369 | 1.7161 | 1.7071 |
| <b>(B) CONS</b> |        |        |        |        |        |        |        |        |
| VAR             | 2.5779 | 2.4832 | 2.4835 | 2.4774 | 2.4624 | 2.4570 | 2.4526 | 2.4712 |
| LBVAR           | 3.0378 | 2.9591 | 2.7831 | 3.1029 | 2.8884 | 4.5131 | 4.9476 | 4.8355 |
| SBVAR           | 2.5889 | 2.6589 | 2.7317 | 2.8299 | 2.8064 | 2.9763 | 3.0847 | 3.1598 |
| DFM             | 2.5800 | 2.4658 | 2.6432 | 2.6095 | 2.5793 | 2.6532 | 2.5458 | 2.5537 |
| FAVAR           | 3.0247 | 2.4908 | 2.6490 | 2.4535 | 2.4839 | 2.4923 | 2.4700 | 2.4720 |
| <b>(C) EMP</b>  |        |        |        |        |        |        |        |        |
| VAR             | 0.7642 | 0.8460 | 0.8434 | 0.8466 | 0.8489 | 0.8478 | 0.8441 | 0.8558 |
| LBVAR           | 0.9280 | 1.0594 | 1.2734 | 1.0617 | 1.0739 | 2.0267 | 2.3253 | 1.2833 |
| SBVAR           | 0.8153 | 0.8349 | 0.8529 | 0.9071 | 0.8962 | 0.9187 | 0.9257 | 0.9802 |
| DFM             | 0.8890 | 0.9133 | 0.8612 | 0.8704 | 0.8966 | 0.9251 | 0.9008 | 0.9013 |
| FAVAR           | 0.8515 | 0.8634 | 0.8501 | 0.8505 | 0.8558 | 0.8483 | 0.8460 | 0.8587 |

The LBVAR performs reasonably only at the very shortest horizons and then deteriorates rapidly, often becoming the worst model as time horizon expanding. This confirms that a full-system BVAR is highly sensitive to dimensionality when the sample is limited. The SBVAR is more stable and clearly outperforms the LBVAR, suggesting that combining variable selection with shrinkage helps in a short-sample, high-dimensional environment.

Factor-type models exhibit the smooth long-run behavior emphasized in the main text. The DFM is never the worst performer and improves relative to the BVARs as the horizon increases. The FAVAR performs particularly well: for GDP and employment it is among the best models at medium and long horizons, and even for consumption it remains competitive.

Finally, the classical VAR performs surprisingly well across all horizons, especially relative to the BVARs. Given Hong Kong's short sample and data volatility, this highlights that simple, low-dimensional models can outperform heavily parameterized systems when shrinkage is insufficient or the signal-to-noise ratio is low.

From a theoretical perspective, long-horizon forecasts tend to converge because idiosyncratic shocks fade and only low-frequency movements matter. Our results confirm this pattern. But in a high-dimensional, short-sample setting, shrinkage alone is often insufficient. The empirical-Bayes pro-

cedure selects a very strong prior ( $\lambda = 0.3$ ), which shrinks coefficients aggressively and can lead to underfitting—useful signals are pushed toward zero, causing the LBVAR to deteriorate quickly. Methods that reduce dimensionality before shrinkage, such as SBVAR and FAVAR, avoid this problem by filtering out noise and retaining only the most informative structure. This explains why they outperform the full BVAR in our environment and suggests that in small open economies, effective dimension reduction is often more important than relying solely on heavy Bayesian shrinkage.

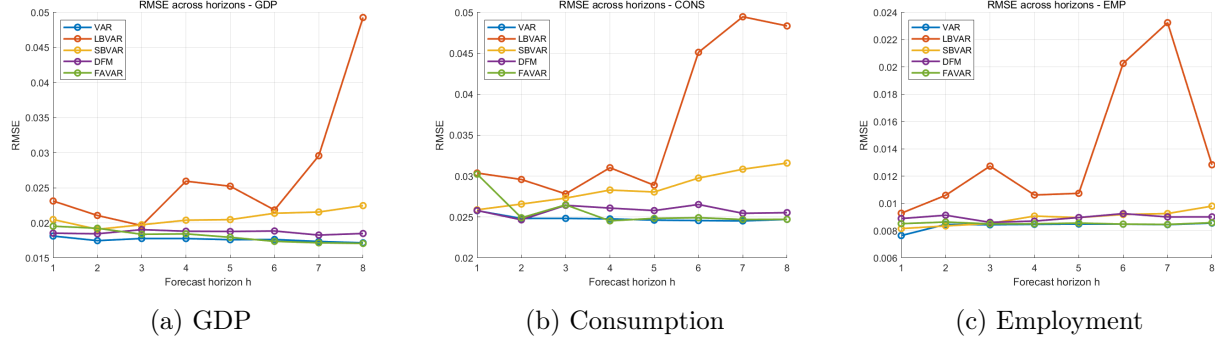


Figure 1: Root Mean Squared Error Across Models and Forecast Horizons

## 4 Limitations and Reflections

Obviously, there are some limitations in this application. The relatively short sample compared to high dimensional data forces shrinkage priors to work aggressively, making full BVARs unstable and reducing the gains from empirical Bayes tuning. Many predictors are monthly or issued with publication delays, but we treat them as clean quarterly series, which means valuable high-frequency signals are lost. Also, structural shocks, including the Global Financial Crisis, and COVID-19, also interact with limited samples in ways that fixed-parameter VARs cannot capture in our models.

Besides, there are some possible improvement methods. Time-varying-parameter VARs or stochastic-volatility VARs might handle structural shifts better, especially in the short run where BVARs deteriorate quickly. Mixed-frequency frameworks could incorporate monthly financial, external, and Mainland indicators more effectively, rather than compressing them into quarterly averages. On the factor side, separating domestic and external blocks or allowing time-varying loadings seems particularly relevant for Hong Kong’s position as a highly open economy.

## Appendix

Table 2: List of Variables and Data Sources

| No. | Name    | Description   | Trans | Data Source                              |
|-----|---------|---|-------|--|
| 1   | GDP     | HK GDP in chained (2023) volume, SA                                     | 5     | Hong Kong Census and Statistics          |
| 2   | CONS    | HK GDP Private Consumption Expenditure in chained (2023) volume, SA     | 5     | Hong Kong Census and Statistics          |
| 3   | PRICONS | HK GDP Private Consumption Expenditure in chained (2023) volume, YoY    | 2     | Hong Kong Census and Statistics          |
| 4   | GOVCONS | HK GDP Government Consumption Expenditure in chained (2023) volume, YoY | 2     | Hong Kong Census and Statistics          |
| 5   | DFCF    | HK GDP Domestic Fixed Capital Formation in chained (2023) volume, YoY   | 2     | Hong Kong Census and Statistics          |
| 6   | INF     | HK CPI-based inflation, SA  | 2     | Hong Kong Census and Statistics          |
| 7   | TOT     | HK terms of trade index, YoY  | 1     | Hong Kong Census and Statistics          |
| 8   | IMP     | HK total imports, YoY   | 1     | Hong Kong Census and Statistics          |
| 9   | EXP     | HK total exports, YoY   | 1     | Hong Kong Census and Statistics          |
| 10  | RPPI    | HK real residential property price index                                | 5     | Federal Reserve Bank of St. Louis        |
| 11  | TPSPA   | Property sale and purchase agreements – total                           | 5     | Hong Kong Land Registry                  |
| 12  | RTPSPA  | Property sale and purchase agreements – residential                     | 5     | Hong Kong Land Registry                  |
| 13  | NTPSPA  | Property sale and purchase agreements – non-residential                 | 5     | Hong Kong Land Registry                  |
| 14  | LF      | Labor force, YoY  | 2     | Hong Kong Census and Statistics          |
| 15  | LFP     | Labor force participation rate  | 2     | Hong Kong Census and Statistics          |
| 16  | UNEMP   | Unemployment rate, SA   | 2     | Hong Kong Census and Statistics          |
| 17  | EMP     | Employed persons, SA  | 5     | Hong Kong Census and Statistics          |
| 18  | M1      | Money supply M1, YoY  | 1     | Hong Kong Census and Statistics          |
| 19  | M2      | Money supply M2, YoY  | 2     | Hong Kong Census and Statistics          |
| 20  | M3      | Money supply M3, YoY  | 2     | Hong Kong Census and Statistics          |
| 21  | EXRATE  | Effective exchange rate index (Jan 2020 = 100)                          | 5     | Hong Kong Census and Statistics          |
| 22  | EXHKUS  | HKD to USD exchange rate  | 5     | Federal Reserve Bank of St. Louis        |
| 23  | EXSZUS  | CHF to USD exchange rate  | 5     | Federal Reserve Bank of St. Louis        |
| 24  | EXJPUS  | JPY to USD exchange rate  | 5     | Federal Reserve Bank of St. Louis        |
| 25  | CPI     | HK CPI, YoY   | 2     | Hong Kong Census and Statistics          |
| 26  | CPIA    | HK CPI A (low expenditure group), YoY                                   | 2     | Hong Kong Census and Statistics          |
| 27  | CPIB    | HK CPI B (medium expenditure group), YoY                                | 2     | Hong Kong Census and Statistics          |
| 28  | CPIC    | HK CPI C (high expenditure group), YoY                                  | 2     | Hong Kong Census and Statistics          |
| 29  | HIB1M   | HKD Interest Settlement Rate, 1M  | 5     | Hong Kong Monetary Authority             |
| 30  | HIB3M   | HKD Interest Settlement Rate, 3M  | 5     | Hong Kong Monetary Authority             |
| 31  | HIB6M   | HKD Interest Settlement Rate, 6M  | 5     | Hong Kong Monetary Authority             |
| 32  | HIB12M  | HKD Interest Settlement Rate, 12M                                       | 5     | Hong Kong Monetary Authority             |
| 33  | DEP1M   | HK deposit rate, 1M   | 5     | Hong Kong Census and Statistics          |
| 34  | DEP3M   | HK deposit rate, 3M   | 6     | Hong Kong Census and Statistics          |
| 35  | DEP6M   | HK deposit rate, 6M   | 5     | Hong Kong Census and Statistics          |
| 36  | DEP12M  | HK deposit rate, 12M  | 6     | Hong Kong Census and Statistics          |
| 37  | SAVRATE | HK savings deposit rate   | 2     | Hong Kong Census and Statistics          |
| 38  | BLEND   | Best lending rate (per annum)   | 2     | Hong Kong Census and Statistics          |
| 39  | LOANS   | Loans and advances, YoY   | 2     | Hong Kong Monetary Authority             |
| 40  | DEPOSIT | HK deposits (HKD and foreign currency)                                  | 5     | Hong Kong Monetary Authority             |
| 41  | HSI     | Hang Seng Index   | 5     | Investing.com                            |
| 42  | HSP     | Hang Seng Property Index  | 5     | Investing.com                            |
| 43  | HSHR    | Hang Seng China Enterprises (H-share) Index                             | 5     | Investing.com                            |
| 44  | CNGDP   | China real GDP, YoY   | 1     | National Bureau of Statistics of China   |
| 45  | CNCPI   | China CPI, YoY  | 2     | National Bureau of Statistics of China   |
| 46  | CNEXP   | China total exports, YoY  | 1     | National Bureau of Statistics of China   |
| 47  | CNIMP   | China total imports, YoY  | 2     | National Bureau of Statistics of China   |
| 48  | CNM1    | China money supply M1, YoY  | 2     | National Bureau of Statistics of China   |
| 49  | CNFXRES | China foreign exchange reserves   | 6     | State Administration of Foreign Exchange |
| 50  | EXCHUS  | RMB to USD spot exchange rate   | 5     | Federal Reserve Bank of St. Louis        |
| 51  | USGDP   | US real GDP (chained), YoY, SA  | 1     | Federal Reserve Bank of St. Louis        |
| 52  | USCPI   | US CPI, YoY, SA   | 2     | Federal Reserve Bank of St. Louis        |
| 53  | USPPI   | US PPI, YoY   | 2     | Federal Reserve Bank of St. Louis        |
| 54  | USIMP   | US imports of goods and services, YoY, SA                               | 1     | Federal Reserve Bank of St. Louis        |
| 55  | USEXP   | US exports of goods and services, YoY, SA                               | 1     | Federal Reserve Bank of St. Louis        |
| 56  | USTRAD  | US trade balance, SA  | 2     | Federal Reserve Bank of St. Louis        |
| 57  | USM1    | US money supply M1, YoY, SA   | 2     | Federal Reserve Bank of St. Louis        |
| 58  | USM2    | US money supply M2, YoY, SA   | 2     | Federal Reserve Bank of St. Louis        |
| 59  | USFFR   | US effective federal funds rate   | 2     | Federal Reserve Bank of St. Louis        |
| 60  | US3MT   | US 3-month Treasury bill rate   | 2     | Federal Reserve Bank of St. Louis        |
| 61  | SPX     | S&P 500 Index   | 5     | Investing.com                            |
| 62  | NASDAQ  | NASDAQ Composite Index  | 5     | Investing.com                            |
| 63  | EXUSUK  | USD to GBP spot exchange rate   | 5     | Federal Reserve Bank of St. Louis        |

Transformation codes: 1 = no transformation; 2 = first difference; 4 = logarithm; 5 = first difference of logarithms; 6 = second difference of logarithms. SA denotes seasonally adjusted series.