

Forecasting in a Small Open Economy: Evidence from Hong Kong

Meishan Deng

University of Bologna

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 2025Q2.¹ 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 variables, 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.

¹ 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
(A) GDP								
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) CONS								
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
(C) EMP								
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.

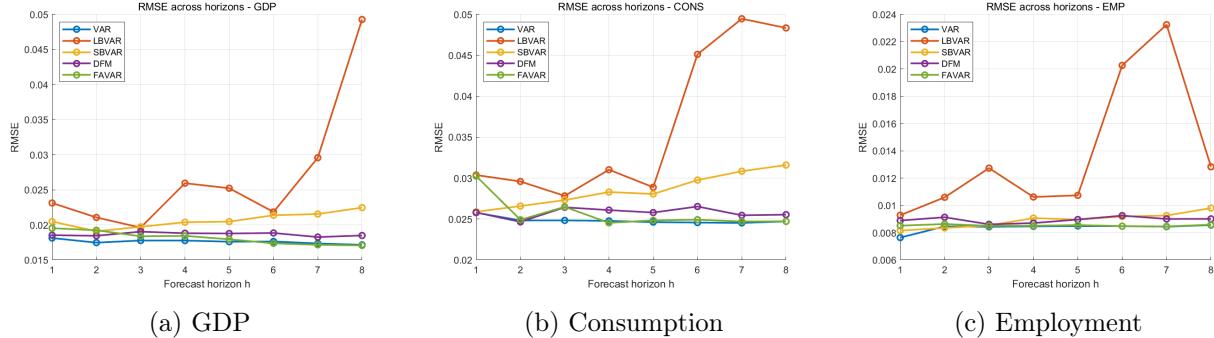


Figure 1: Root Mean Squared Error Across Models and Forecast Horizons

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	CNXFRES	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.