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Modeling Multi-Source Economic Dependencies in the Guangdong-Hong Kong-Macao Greater Bay Area Using LSTM Networks

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Abstract

In research on the economic connectivity structure and industrial synergetic development of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA), characterizing the temporal evolution of intercity economic linkages is essential for revealing the intrinsic mechanisms of regional integration and the dynamic patterns of industrial-chain collaboration. Traditional time-series approaches, such as autoregressive integrated moving average (ARIMA) and vector autoregression (VAR), have exhibited strong robustness in univariate and linear multivariate settings since their systematic development by Box and Jenkins in the 1970s. However, when confronted with the nonlinear dependence, long-memory effects, and heterogeneous multi-source interactions that commonly arise in economic networks, such methods often suffer from limited expressive power.

Keywords

Guangdong-Hong Kong-Macao Greater Bay Area (GBA) , Economic connectivity structure, Industrial synergetic development, Time-series methods (ARIMA/VAR), Nonlinearity and complex network features.

1. Introduction

To overcome the gradient vanishing and exploding problems that conventional recurrent neural networks face in long-sequence learning, Hochreiter and Schmidhuber proposed the Long Short-Term Memory (LSTM) architecture in their 1997 paper "Long Short-Term Memory," published in Neural Computation. Hochreiter and Schmidhuber (1997) systematically proposed the long short-term memory (LSTM) network, which effectively alleviates the vanishing gradient problem in traditional recurrent neural networks through a gated architecture and provides an important foundation for time-series forecasting and sequence modeling. [1] The central idea of their study was that, by introducing memory cells and gate-control mechanisms into the hidden-state transmission pathway, error information could flow along the time dimension in an approximately constant manner, thereby enabling stable learning of dependencies that span long time horizons. Specifically, the architecture contains three gates: the input gate regulates the extent to which new information is written into the memory cell; the forget gate controls the retention or removal of previously stored information; and the output gate determines how much information in the memory cell is exposed to the external layer at the current time step. Together, these components provide dynamic management of writing, storing, and reading, allowing the network to capture short-run fluctuations while preserving long-run dependencies reliably.

This seminal work also introduced the concept of the constant-error carousel (CEC), which ensures that gradients do not decay excessively during backpropagation through time. Through a series of benchmark tasks involving long time lags, the authors demonstrated the substantial

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advantage of LSTM over ordinary RNNs in learning long-term dependence. Gers et al. (2000) further introduced the forget gate into the LSTM architecture, enabling the model to automatically control the retention and discarding of historical information and thereby improving its ability to learn non-stationary sequences and long-term dependencies.[2] Subsequent work by Gers, Schmidhuber, and Cummins further incorporated the forget gate, enabling the network to reset its memory rapidly when the environment or task changes. In the following years, the connectivity patterns of gates and the capacity for temporal representation were further extended, establishing LSTM as one of the mainstream tools for modeling long sequences and nonlinear dependencies.The basic structure of the LSTM can be formalized as follows:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = t(W_C[h_{t-1}, x_t] + b_C)$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot t(C_t)$$

Here, x_t denotes the input vector, which may include a city's historical GDP, neighboring cities' economic indicators, and the intensity of institutional collaboration; h_t denotes the hidden-state vector; C_t denotes the cell state; $\sigma(\cdot)$ is the sigmoid function; $\odot$ represents the Hadamard element-wise product; and W and b denote the weight matrices and bias vectors, respectively. Graves et al. (2013) applied deep recurrent neural networks to speech recognition and demonstrated the effectiveness of deep RNN/LSTM architectures in extracting complex sequential features and modeling high-dimensional time-series data, providing methodological support for their application to economic forecasting.[3] Since its introduction in 1997, LSTM has undergone multiple rounds of structural optimization and functional expansion. In 2000, Gers et al. first incorporated the forget gate into the original LSTM framework in Neural Computation, significantly improving the efficiency and adaptability of memory updating under non-stationary environments. Between 2013 and 2014, Graves demonstrated the effectiveness of LSTM in complex sequence tasks such as speech recognition and sequential generation, thereby confirming its broad cross-domain applicability and consolidating its status as a leading method for long-sequence modeling. In recent years, as regional economic data have rapidly increased in both temporal resolution and multivariate structure, LSTM has been widely adopted in regional economic forecasting, energy-demand analysis, and financial risk assessment, becoming an important methodological tool for characterizing multi-layer interactions among temporal, spatial, and institutional mechanisms. Li et al. (2024) examined changes in economic network patterns and their influencing factors in the Guangdong–Hong Kong–Macao Greater Bay Area, revealing spatial differentiation characteristics and driving mechanisms in the evolution of regional economic networks.[4]

Zhang et al. (2025) employed a PCA–ARIMA–LSTM hybrid model to forecast the economic development of the Guangdong–Hong Kong–Macao Greater Bay Area, suggesting that combining traditional statistical models with deep learning methods can improve the explanatory power and fitting performance of regional economic time-series forecasting.[5] In the present study, LSTM is introduced as the core forecasting method for the dynamic analysis of the GBA economic network for two main reasons. First, LSTM exhibits clear advantages in handling economic time-series data with long-range dependence, making it possible to integrate a city's own economic inertia with intercity linkage effects within a unified model structure while avoiding premature information decay over long time spans. Second, the model can jointly embed exogenous features such as economic distance and institutional collaboration together with historical economic trajectories, thereby providing higher structural resolution

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and stronger sensitivity to the evolution of regional economic connectivity and industrial synergetic development. This, in turn, offers a more precise quantitative basis for policy evaluation and scenario simulation.

2. Methodology

Tang et al. (2022) investigated the evolution of economic patterns and urban network systems in the Guangdong–Hong Kong–Macao Greater Bay Area, showing that intercity economic linkages exhibit clear characteristics of networking, hierarchy, and core-city agglomeration.[6] After establishing the theoretical basis and research motivation for introducing the LSTM model, this study constructs a benchmark framework for single-city time-series forecasting using annual GDP data for 11 cities in the Guangdong-Hong Kong-Macao Greater Bay Area from 2000 to 2023. The model takes each city's GDP series over the most recent five years as input in order to capture economic inertia and predict GDP in the following year. The time-window length is set to five periods. Min-Max normalization is performed using only the training set to avoid leakage of future information, and the data are strictly partitioned into training and testing sets in chronological order at a ratio of 8:2. The model architecture consists of a single LSTM layer, a Dropout layer, and a fully connected output layer. Mean squared error (MSE) is used as the loss function, and the Adam optimizer is employed for parameter updating. During training, a sliding-window scheme is combined with early stopping to suppress overfitting and improve generalization. This setup effectively captures the nonlinear temporal dependence of the regional economic network and provides a robust benchmark for subsequent model extensions with covariates and for comparative evaluation. For convenience in subsequent modeling and comparative analysis, let the annual gross domestic product of city i in year t be denoted by $y_{i,t}$ and normalized as follows:

$$\tilde{y}_{i,t} = \frac{y_{i,t} - y^{m_{i,tr}}}{y^{m_{i,tr}} - y^{m_{i,tr}}}, t = 1, \ldots, T$$

where

$$y^{m_{i,tr}} = m_{t \le t_{tr}} y_{i,t}, y^{m_{i,tr}} = m_{t \le t_{tr}} y_{i,t}$$

and the scaling interval is determined solely from the training sample. Using a sliding time window of length L, the input vector is constructed as

$$x_{i,t} = \left(\tilde{y}_{i,t-L+1}, \tilde{y}_{i,t-L+2}, \ldots, \tilde{y}_{i,t}\right) \in \mathbb{R}^L$$

with the prediction target being the normalized value in the next period. The benchmark model A (single-city LSTM baseline) is expressed as

$$h_{i,t} = LSTM_{\Theta}(x_{i,t}), \hat{s}_{i,t+1} = w^{\top} h_{i,t} + b$$

where $x_{i,t}$ is the input vector for city i in year t, containing an L-length GDP history sequence, and $h_{i,t} \in \mathbb{R}^H$ denotes the LSTM hidden state, while w and b are the parameters of the output layer. The internal state updates of the LSTM unit can be written as

$$f_{i,t} = \sigma\left(W_f\left[h_{i,t-1}, x_{i,t}\right] + b_f\right), i_{i,t} = \sigma\left(W_i\left[h_{i,t-1}, x_{i,t}\right] + b_i\right)$$

$$\tilde{C}_{i,t} = t\left(W_C\left[h_{i,t-1}, x_{i,t}\right] + b_C\right), C_{i,t} = f_{i,t} \odot C_{i,t-1} + i_{i,t} \odot \tilde{C}_{i,t}$$

$$o_{i,t} = \sigma\left(W_o\left[h_{i,t-1}, x_{i,t}\right] + b_o\right), h_{i,t} = o_{i,t} \odot t\left(C_{i,t}\right)$$

The normalized GDP prediction is given by

$$y_{i,t+1} = \hat{s}_{i,t+1}$$

and the training objective is to minimize mean squared error:

$$\mathcal{L} = \frac{1}{N} \sum \left(y_{i,t+1} - \tilde{y}_{i,t+1}\right)^2$$

Residuals on the test set are computed as

$$e_{i,t} = y_{i,t} - \hat{y}_{i,t}$$

and the evaluation metrics are defined as follows:

$$RMSE_i = \sqrt{\frac{1}{n_i}\sum e_{i,t}^2}$$

$$MAE_i = \frac{1}{n_i}\sum \parallel e_{i,t} \parallel, where\ R_i^2 = 1 - \frac{\sum e_{i,t}^2}{\sum \left(y_{i,t} - \bar{y}_i\right)^2}$$

Based on the above setup, baseline single-city LSTM forecasting models are first established for the 11 cities in the GBA, and rolling-window prediction is conducted using GDP series from 2000 to 2023. The model inputs are each city's GDP values over the most recent L years, and the output is the predicted GDP in the next year. The aggregate predictive performance is reported in Table 6.22, which presents RMSE, MAE, and R^2 for the test period.

Overall, Dongguan exhibits the best predictive performance, with an R^2 value as high as 0.668, indicating that its GDP growth trajectory can be explained to a considerable extent by its own historical information. By contrast, the R^2 values for core and outward-oriented cities such as Guangzhou, Shenzhen, Hong Kong, and Macao are negative, implying that their economic fluctuations are driven to a large extent by intercity linkages and exogenous shocks, which cannot be adequately captured by a univariate city-specific historical sequence alone. This phenomenon reveals structural differences across cities in terms of economic driving forces and sources of volatility.

Behind these performance differences, the distribution of prediction errors across time and space is analytically meaningful. As shown in the figure, Guangzhou and Shenzhen display pronounced negative residuals in multiple years, especially during 2022-2023, when concentrated and substantial systematic underprediction occurs. This suggests that the actual expansion of the two cities during that period considerably exceeded the level that the model could infer from historical inertia alone, reflecting the combined influence of external demand and cross-regional linkage effects. By contrast, manufacturing-oriented cities such as Zhaoqing, Jiangmen, and Zhongshan exhibit much smaller residual fluctuations, and the predicted values are much closer to the actual values. This indicates that their economic development paths are more consistent with past trends and are less affected by idiosyncratic shocks, thereby enabling the model to achieve stronger explanatory power and robustness in such cities.

Feng et al. (2022) constructed a complex network model of the Guangdong–Hong Kong–Macao Greater Bay Area based on an economic development index, providing a network-based perspective for evaluating the strength of intercity economic linkages and regional coordinated development.[7] To further uncover the interrelations among forecasting errors across cities, the figure presents the correlation matrix of the raw residuals. The results show that residuals among major manufacturing cities such as Foshan, Jiangmen, Zhuhai, and Zhongshan are highly positively correlated, with coefficients close to 1, indicating strong synchronous fluctuations along the regional industrial chain. In other words, under similar macroeconomic shocks or industry-cycle changes, the prediction deviations of these cities tend to move in the same direction. By contrast, Guangzhou and Shenzhen are mostly characterized by significantly negative residual correlations with manufacturing cities, suggesting that their economic volatility is primarily driven by trade, finance, and high-end services, and that their responses to external shocks often differ from those of manufacturing-based cities. Macao, meanwhile, exhibits relatively low correlations with most other cities, further confirming that its tourism- and gaming-dominated industrial structure occupies a comparatively independent position in the regional economy.

Huang et al. (2021) explored the relationship between logistics network construction and economic linkage development in the Guangdong–Hong Kong–Macao Greater Bay Area from a spatial perspective, indicating that logistics channels and spatial connectivity are important supports for regional economic coordination.[8] On this basis, Table 1 reports the mean absolute residual and the standard deviation of the absolute residual for each city in order to quantify the magnitude and stability of forecasting errors. The results show that Zhaoqing, Jiangmen, and Zhongshan have relatively small residual levels and limited fluctuation, which further confirms the good adaptability of the model to manufacturing cities with comparatively stable growth paths. By contrast, Guangzhou and Shenzhen show both large residual means and high volatility. Even when the overall RMSE remains within an acceptable range, clear systematic errors persist, indicating the limitations of a single time-series model in capturing the complex dynamics of core outward-oriented cities.

Table 1 Mean and standard deviation of absolute residuals

City	Mean absolute residual	SD of absolute residual
Zhaoqing	5,800,938	2,929,991
Zhuhai	8,423,832	10,607,620
Jiangmen	8,737,041	6,453,879
Zhongshan	10,980,820	5,633,798
Dongguan	11,302,500	14,616,710
Huizhou	13,152,480	7,311,502
Foshan	18,652,940	12,558,950
Hong Kong	25,315,370	24,781,000
Macao	38,321,610	11,861,310
Guangzhou	84,795,400	54,752,300
Shenzhen	94,491,190	84,434,490

Considering that the systematic bias described above may originate from annual common fluctuations shared across cities, this study removes the annual common factor from the prediction residuals of the single-city LSTM model. Specifically, for the residual of city i in year t, the cross-city mean residual in that year, interpreted as the annual common factor, is first calculated as

$$\bar{e}_t = \frac{1}{N}\sum e_{i,t}$$

and then subtracted from the raw residual to obtain the corrected residual:

$$e_{i,t} = e_{i,t} - \bar{e}_t$$

This procedure effectively removes the annual synchronous fluctuation shared by cities, thereby allowing a more precise characterization of intercity heterogeneity. The results indicate that Zhongshan, Huizhou, Jiangmen, Zhaoqing, and Foshan exhibit residual correlations generally above 0.90, forming a highly consistent manufacturing collaboration cluster. This suggests strong synchronicity among manufacturing cities with respect to industrial-chain fluctuations and supply-demand cycles, thereby highlighting the important role of industrial-structure homogeneity and the intensity of regional division of labor in the transmission of forecasting errors. By contrast, Guangzhou and Shenzhen display markedly negative residual correlations with most manufacturing cities, indicating a systematic divergence between core service- and high-end-manufacturing centers and the manufacturing cluster in their paths of economic fluctuation. This difference may stem from the distinct response mechanisms of outward-oriented economic structures when confronted with external shocks. In addition, Macao shows absolute correlation coefficients below 0.80 with most cities, suggesting a relatively high degree of independence, which is consistent with its tourism- and gaming-centered economic structure and its weaker linkage to the broader regional industrial cycle.

3. Discussion

Lee and Lin (2020) analyzed the Guangdong–Hong Kong–Macao Greater Bay Area from the perspective of economic complexity, emphasizing that industrial structural complexity and urban functional specialization are key factors affecting the economic competitiveness of the city cluster.[9] The previous analysis of the spatial distribution of residuals and cluster characteristics suggests two central facts. On the one hand, forecasting errors exhibit significant same-direction clustering across several secondary cities dominated by manufacturing. On the other hand, core outward-oriented cities such as Guangzhou and Shenzhen display systematic divergence from this "manufacturing belt." This implies that the benchmark LSTM model (Model A), which relies solely on each city's own historical series, cannot explicitly absorb two types of linkage mechanisms that are equally important in the regional economy: first, spatial spillovers generated by geographical proximity, including factor mobility, supply-chain coupling, and the transmission induced by commuting and logistics networks; second, institutional coordination created by intercity arrangements, such as cooperation agreements, integrated planning, port facilitation, and fiscal or industrial policy coordination, all of which exert persistent effects on transaction costs. At the same time, the presence of annual common-factor errors indicates that there also exist synchronous cross-city and cross-industry shocks that have not been captured by the model. Accordingly, two categories of exogenous covariates are introduced on top of Model A in order to strengthen the characterization of regional structural differentiation and common shocks.

Spatial covariates are constructed using the intercity distance matrix or a spatial weight matrix to characterize physical proximity and connectivity intensity. Specifically, a row-stochastic distance weight is defined as

$$w_{ij}^{(d)} = \frac{d_{ij}^{-\alpha}}{\sum d_{ij}^{-\alpha}}, j \neq i$$

where d_{ij} is the driving distance between cities i and j, and α controls the speed of distance decay, commonly set to 1 or 2. This yields a distance-weighted GDP of neighboring cities:

$$G_{i,t}^{(d)} = \sum w_{ij}^{(d)} \, y_{j,t-1}$$

where $y_{j,t-1}$ is the GDP of city j in the lagged period, ensuring that only known information is used when forecasting year $t+1$.

Institutional covariates are constructed from an institutional cooperation intensity matrix, based on evaluations of cooperation agreements, joint planning, customs facilitation, cross-boundary infrastructure, and related factors. A row-stochastic institutional weight is defined as

$$w_{ij}^{(z)} = \frac{z_{ij}}{\sum z_{ij}}, j \neq i$$

which gives the institutionally weighted GDP as

$$G_{i,t}^{(z)} = \sum w_{ij}^{(z)} \, y_{j,t-1}$$

This specification can further be combined with annual policy-event dummy variables to absorb strong annual resonance generated by major plans, pandemic shocks, or other systemic disturbances. Intuitively, the spatial channel captures demand and supply transmission in the physical network, whereas the institutional channel reflects the reduction of institutional frictions and the amplification of coordination effects in the institutional network. The two channels are complementary and correspond, respectively, to the "same-direction

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manufacturing cluster" and the "inverse or independent fluctuations of core cities" identified in the residual analysis.

In the empirical implementation, these two categories of covariates are introduced in lagged form together with each city's historical window into the LSTM. Sequence components first extract hidden representations, which are then concatenated with the spatial and institutional covariates in the fully connected layer to complete the prediction. All numerical features are normalized via Min-Max scaling using only the training segment to prevent data leakage. On this basis, Model B (spatial covariates only), Model C (institutional covariates only), and Model D (spatial plus institutional covariates) are constructed to test the marginal contributions of the two transmission channels and their joint effect on forecasting accuracy and robustness. This design not only reduces the proportion of annual common-factor variation remaining in the residuals, but also explicitly embeds the structural differentiation among clusters, core cities, and relatively independent units into the forecasting framework. Accordingly, the three extended models are defined as follows. Model B (spatial covariates only) is

$$\hat{y}_{i,t+1}^{(B)} = F\left(x_{i,t}, G_{i,t}^{(d)}\right)$$

That is, spatial covariates are added to the baseline LSTM input through distance-based or spatially weighted neighboring GDP so as to capture transmission effects induced by geographic proximity. Model C (institutional covariates only) is

$$\hat{y}_{i,t+1}^{(C)} = F\left(x_{i,t}, G_{i,t}^{(z)}, P_t\right)$$

Institutional covariates, including the institutional cooperation index and policy-event dummies, are incorporated to reflect the roles of institutional coordination and policy shocks.Model D (spatial + institutional covariates) is

$$\hat{y}_{i,t+1}^{(D)} = F\left(x_{i,t}, G_{i,t}^{(d)}, G_{i,t}^{(z)}, P_t\right)$$

This model simultaneously includes spatial and institutional information in order to capture the dual transmission mechanisms of physical proximity and institutional cooperation. Here, $x_{i,t}$ denotes the historical economic feature vector of city i at time t, including GDP, investment, consumption, industrial structure, and related variables, while the normalized prediction can be mapped back to the original scale via inverse normalization:

$$\hat{y}_{i,t+1} = y_{i,t+1}(y^{m_{i,tr}} - y^{m_{i,tr}}) + y^{m_{i,tr}}$$

This design allows the effects of different covariate combinations on forecasting accuracy and robustness to be evaluated within a unified framework. To compare the predictive gains generated by different types of exogenous covariates, this study extends the benchmark Model A by introducing spatial covariates (Model B), institutional covariates (Model C), and combined spatial plus institutional covariates (Model D), and evaluates performance using R^2. Table 2 reports the R^2 values of the 11 cities under the four models and identifies the best-performing specification for each city.

Table 2 City-specific R^2 under different extended models and the optimal model

City	A	B	C	D	Best model	Best R^2
Dongguan	0.6768	-1.9829	-1.1482	0.7365	D	0.7365
Zhongshan	-37.8245	-33.9005	-8.7987	-11.1135	C	-8.7987
Foshan	-0.4860	0.7552	0.6394	0.7025	B	0.7552
Guangzhou	-3.3349	-2.7482	-1.4061	-8.9980	C	-1.4061
Huizhou	-7.4209	-2.4538	-6.7390	-2.2936	D	-2.2936
Jiangmen	-0.6841	0.8812	0.9382	0.8774	C	0.9382
Shenzhen	-0.6426	-4.9890	-2.7103	0.8780	D	0.8780
Macao	-13.8631	-7.7568	-5.0292	-6.2503	C	-5.0292
Zhuhai	-1.7698	-3.6188	-8.3739	-3.9391	A	-1.7698
Zhaoqing	-17.4393	-6.7711	-6.3546	-6.0499	D	-6.0499
Hong Kong	-0.5367	-10.5106	-7.3176	-0.9791	A	-0.5367

Table 2 shows clear heterogeneity in the optimal covariate type across cities. Model B (spatial covariates) performs best for Foshan, indicating that manufacturing nodes characterized by industrial agglomeration and tight connections with surrounding cities rely more strongly on geographic proximity information for forecasting improvement. Model C (institutional covariates) yields the highest R^2 values in Zhongshan, Guangzhou, Jiangmen, and Macao, confirming that institutional cooperation and policy factors play a substantial role in core and sub-core cities, especially those with stronger institutional linkage intensity. Model D (spatial plus institutional covariates) performs best in Dongguan, Huizhou, Shenzhen, and Zhaoqing, suggesting that the superposition of the two channels is helpful for capturing composite economic linkages simultaneously driven by geographic proximity and institutional coordination. By contrast, Model A (the baseline LSTM) remains optimal for Zhuhai and Hong Kong, implying that their economic fluctuations are more strongly dominated by internal factors, and that the incremental gain from external spatial and institutional covariates is comparatively limited. Overall, this differentiated pattern of model fit indicates that regional economic forecasting should flexibly select single or combined covariates in accordance with a city's industrial structure, network position, and institutional linkage intensity so as to achieve a better balance between model complexity and predictive performance.

Zhao and Wei (2020) examined the spatial structure of the Guangdong–Hong Kong–Macao Greater Bay Area as an emerging megacity region, highlighting the importance of spatial restructuring, urban hierarchy, and cross-boundary governance in the formation and development of the region.[10] To further illustrate the gains generated by different covariate types, the improvement in R^2 of each city's best-performing model relative to the benchmark Model A, namely $\Delta R^2 = R_{best}^2 - R_A^2$. The results indicate that cities such as Zhongshan, Zhaoqing, and Macao obtain substantial improvements after the introduction of institutional covariates or the combined spatial-institutional specification. In particular, Zhongshan achieves an increase of 29.03 percentage points, indicating that institutional factors play a crucial role in forecasting this category of city. Foshan, by contrast, obtains an evident improvement after introducing spatial covariates, suggesting that its economic fluctuations are highly dependent on linkage effects with neighboring cities. Conversely, the gains for Zhuhai, Shenzhen, Dongguan, and Hong Kong are close to zero, indicating that external spatial or institutional information has limited short-term predictive value for these cities, and that the model primarily relies on internal time-series characteristics. This result is consistent with the preceding table-based analysis and further highlights the importance of regional heterogeneity for model performance.

4. Conclusion

The overall findings suggest that different types of covariates play markedly different roles in regional economic forecasting, reflecting the strong heterogeneity of GBA cities in industrial structure, spatial connection, and institutional environment. First, the spatial synergetic effect of manufacturing clusters plays a key role in enhancing regional economic resilience. For a manufacturing hub such as Foshan, the introduction of spatial covariates substantially improves predictive performance, indicating that its economic fluctuations are highly dependent on physical linkages and factor exchanges with upstream and downstream cities in the industrial chain. This finding underscores the importance of further improving cross-city transportation, logistics, and information-transmission networks so as to reduce the risk of industrial-chain disruption.

Second, the independent volatility of core cities deserves particular attention. The gains obtained by Guangzhou and Shenzhen after the inclusion of external spatial and institutional information remain limited, indicating that their economic dynamics are more strongly driven by higher-order external factors such as adjustments in global production networks, technological innovation cycles, and fluctuations in international markets. For such cities, it is difficult to achieve substantial predictive improvement through regional internal covariates alone. Future model construction should therefore incorporate international macroeconomic variables, technology-cycle indicators, and cross-border capital-flow data in order to better capture the mechanisms behind their volatility.

Third, institutional coordination exerts a particularly strong promoting effect in several sub-core cities. Zhongshan, Jiangmen, and Macao obtain significant forecasting improvements after the introduction of institutional covariates, confirming the importance of cross-city institutional integration, policy coordination, and business-environment optimization for regional synergetic development. Institutional coordination can not only reduce the time costs generated by institutional frictions, but can also enhance the efficiency of factor mobility through mechanisms such as standard harmonization and mutual policy recognition, thereby amplifying the economic returns to regional cooperation.

In summary, spatial linkage, spillovers from core cities, and institutional coordination constitute the three major pillars driving synergetic development in the Guangdong-Hong Kong-Macao Greater Bay Area. In terms of policy design, manufacturing-cluster cities should continue to optimize cross-city transportation and industrial-chain layout in order to strengthen resilience against shocks; core cities should develop stronger spillover mechanisms to guide the diffusion of technology, capital, and high-end services to surrounding cities, thereby forming a multi-level growth-pole system; and, at the institutional level, regional integration should be deepened through a unified market-access regime, common standards, and shared public-service platforms. At the same time, in economic forecasting and policy evaluation, spatial, institutional, or combined covariates should be selected flexibly according to each city's industrial base, network position, and institutional environment, so as to attain a better balance between model complexity and predictive performance while enhancing both regional resilience and global competitiveness.

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