

Differentiated Responses of Major Korean Ports to Macroeconomic Conditions: Container Throughput Forecasting and Management Strategies

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Abstract: Maritime transport carried 99.7% of Korea's international cargo in 2023, and container throughput at Korean ports moves with economic conditions abroad. This study identifies the macroeconomic indicators that move throughput at Busan Port, Incheon Port, and Gwangyang Port, and carries those indicators into forecasting models built for each port. A common candidate set and selection procedure were applied to the three ports and to their combined total over 120 monthly observations from January 2013 to December 2022, so that differences in the estimates follow from the ports rather than from model specification. Significant variables entered ARIMAX, SARIMAX, LSTM, and Bi-LSTM models as exogenous regressors, trained on 84 months and tested on the 36 months from January 2020. Interaction and squared terms were estimated for the combined total. The base interest rate, the economic growth rate of China, and the SCFI carried negative coefficients for the combined total, Busan Port, and Incheon Port. At Gwangyang Port both Chinese growth and the SCFI carried positive coefficients, and the interest rate did not enter the final model. LSTM produced the lowest RMSE and MAPE at every port, with MAPE between 4.67% and 7.91%. The interaction between the interest rate and Chinese growth was negative, so throughput falls furthest when both run high. Because response directions differ across ports, a forecast aggregated across ports gives weak support for port-level planning. The findings were consolidated through a SWOT analysis of port conditions, and four scenarios over the two interacting indicators are proposed as a basis for differentiated response by port.

Keywords: Container throughput, port cargo mix, macroeconomic determinants, regression analysis, time series forecasting, port management strategy, SWOT analysis.

1. INTRODUCTION

The foreign trade of the Republic of Korea depends on maritime transport, and this dependence exposes the country to geopolitical risk. The armistice with the Democratic People's Republic of Korea has held since the Korean War ended in 1953. Land routes to the north have stayed closed throughout this period. Maritime transport therefore carries greater weight than in most other countries. International cargo carried by sea reached about 1.32 billion tons in 2023. Sea transport handled 99.7% of all international cargo in that year [1]. Trade also accounts for a large share of the national economy. Foreign trade dependency measures the ratio of exports and imports to gross domestic product (GDP). The ratio for Korea stood at 92.8% in 2025 [2]. An economy with this structure stays vulnerable to conditions abroad. Ports form the channel through which shocks from geopolitical risk enter the domestic economy. Ports also show the state of trade at an early stage. The role of a port reaches beyond

cargo handling. A port works as a gateway of the national economy and as a node in the global supply chain [3]. When conditions abroad shift, freight rates and shipping routes change first. The change then appears in port throughput. Busan Port, Incheon Port, and Gwangyang Port are the main ports of Korea. These three ports work as points where trade conditions can be read in advance.

Throughput forecasts serve as a key basis for investment and operation plans at ports. A port is infrastructure that takes large capital over a long period. The size of berths and the number of cargo handling equipment are set from forecasts of future throughput [4]. Forecast accuracy is closely tied to the efficient use of budgets. Timely port development supports the logistics competitiveness of the nation. Throughput also guides short-term operation. Berth allocation, equipment placement, and staffing all draw on expected volumes. Port throughput responds to many outside factors, and this response makes forecasting difficult. Throughput reacts quickly to rapid changes in economic and social conditions [4]. Large shocks bring sharp swings in volume. World container throughput fell by 9.7% from the previous year in 2009, following

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the global financial crisis [5]. The COVID-19 pandemic of 2020 widened these swings by disrupting supply chains. The war between Russia and Ukraine in 2022 forced a redrawing of shipping routes for energy and grain [6].

The difficulty of forecasting comes from the composition of cargo as well as from outside shocks. Korean forecasting practice already separates the two types of container cargo. Import and export volumes are forecast at the national level from domestic gross domestic product and then allocated to each port. Transshipment volumes are forecast port by port from the gross domestic product of China, the United States, and Japan, and the results are summed afterward [4]. The split reflects a view that the two types of cargo respond to different conditions. Each port handles both types together, and the mix differs across ports. Transshipment cargo made up 56.7% of throughput at Busan Port in 2025. The shares at Gwangyang Port and Incheon Port were 12.1% and 1.1% [7]. A port with a high transshipment share depends on the route decisions of shipping lines. A port with a high gateway share depends on the trade activity of domestic shippers. Berths, equipment, and staff at a port serve both types of cargo together, so operating plans rest on the volume of both types combined. Throughput at one port therefore need not move in the same direction as throughput at another. Decisions on port operation and investment are made port by port, so a single national measure can work against its purpose at some ports.

This study examines how macroeconomic indicators affect container throughput at each of the main Korean ports. The study then proposes management strategies by port type. Four analyses were carried out for this purpose. Regression analysis was applied to each port to find the significant factors and the direction of their effects. The factors found in this step were entered as exogenous variables in time series forecasting models. Models were built for each port, and forecast errors were compared across ports. Interaction and nonlinear relationships among the factors were examined for total throughput. This step covers effects that individual factors cannot explain on their own. Management strategies by port type and scenarios by economic condition were drawn from these results.

This paper has five sections. Section 2 reviews prior work on the factors behind port throughput and on forecasting methods. Section 3 describes the data and the analytical methods. Section 4 presents the results and reads the differences among ports. Section 5 summarizes the findings, notes their implications, and discusses the limitations.

2. LITERATURE REVIEW

2.1. Determinants of Port Container Throughput

Ports function as gateways of national economies and as critical nodes within global supply chains [3]. Because throughput reflects the aggregate outcome of trade activity, a substantial body of research has sought to identify the factors that govern its variation. The determinants examined in prior work can be organized into five groups.

Macroeconomic activity indicators constitute the most widely adopted group. Gross domestic product, economic growth rates, industrial production indices, and consumer price indices have been employed on the premise that throughput responds to the overall scale of production and trade [8-14]. A recurring observation within this group is that the dominant determinant varies with the port under examination. Comparative work on Chinese ports has reported that consumer goods sales and fixed asset investment exerted the strongest influence at different ports within the same country [11].

Monetary and financial indicators have been examined as channels operating through price competitiveness and corporate financing conditions. Exchange rate volatility has been associated with contraction in Korean container throughput [15]. Foreign direct investment has also been used to explain structural change in logistics sectors and port hinterlands [16].

Shipping market indicators capture supply and demand conditions in maritime transport more directly. Studies addressing the interrelations among the Baltic Dry Index, the Shanghai Containerized Freight Index, and crude oil prices have accumulated over the past two decades [17-19], with applications extending to Korean ports [20-21]. Work on the COVID-19 lockdowns has further shown that the contraction in container throughput ranged from 7.1% to 30.9% depending on the port examined [22].

Logistics capability and institutional indicators address service levels, customs procedures, and infrastructure quality. Port service, hinterland conditions, and connectivity have been identified as determinants of competitiveness among Northeast Asian ports, and the World Bank Logistics Performance Index has been applied to national trade performance [23-24].

Geopolitical risk indicators represent the most recent addition to this literature. Following the development of a text-based Geopolitical Risk Index [25], subsequent work has examined its effects on

crude oil prices and freight rates [26-27], on short-term movements in shipping freight [28], on crude oil supply security [29], and on freight volumes across transport modes [30]. Evidence specific to Korea indicates that national import and export volumes are particularly sensitive to geopolitical risk, with effects varying by trading partner [31].

2.2. Forecasting and Analytical Approaches to Port Throughput

Alongside the identification of determinants, methodological development has proceeded toward forecasting throughput over time. Two broad streams are discernible. The first stream comprises traditional statistical models that represent autoregressive structure and seasonality explicitly. Autoregressive integrated moving average specifications extended with exogenous regressors have been applied to port throughput, often in combination with dimension reduction techniques that condense large sets of macroeconomic indicators [10, 12]. Seasonal specifications incorporating industrial production as an exogenous variable have likewise been employed for inland container volumes [32]. Models in this stream offer interpretable structure and accommodate external indicators, but rest on assumptions of linearity and explicit seasonality that constrain their response to nonlinear patterns and structural breaks.

The second stream comprises machine learning and deep learning approaches, adopted on the premise that the dynamics of logistics systems are inherently nonlinear. A fuzzy information granulation approach was introduced for freight volume prediction [33], and artificial neural networks and support vector regression have been benchmarked against conventional statistical models [34-35]. More recently, long short-term memory (LSTM) architectures capable of learning long-range dependencies have been applied to container throughput, with bidirectional variants examined alongside conventional models [14, 36-37].

Comparative evidence between the two streams is not uniform. Support vector regression and autoregressive models have been reported to capture nonlinear relationships at comparable levels on small datasets, and regression models have outperformed neural networks for commodity groups exhibiting sustained upward trends while the reverse held for irregular series [34]. The evidence indicates that model suitability depends on the scale and volatility characteristics of the data rather than on the model class alone. Root mean square error (RMSE) and mean absolute percentage error (MAPE) have served as the principal evaluation criteria across both streams [14, 36].

2.3. Summary and Research Gap

Studies that model container throughput at Korean ports have centered on Busan Port [14, 20, 21, 37] or on the national total [15]. National forecasting practice separates import and export cargo from transshipment cargo and forecasts the two with different indicators [4]. The split rests on the view that the two types of cargo respond to different conditions. Qualitative assessments have also described distinct facility conditions, hinterland characteristics, and competitive positions at Busan Port and Gwangyang Port [38, 39]. These assessments used SWOT and analytic hierarchy process frameworks and did not measure how throughput responds to economic conditions. Studies of several ports elsewhere have reported different results across ports without tracing the difference to port characteristics [11, 22]. None of the studies reviewed here compares the three main Korean ports under one set of variables and one estimation procedure, although the three differ widely in cargo mix.

A second gap lies between the analysis of determinants and the construction of forecasting models. Studies of determinants have focused on the sign and size of coefficients, and forecasting studies have focused on predictive accuracy. Where the two have been joined, large sets of indicators have been condensed into a few factors before entering the forecasting model [10, 12]. The factors can improve accuracy but no longer correspond to named indicators, so the forecasting model cannot be read against the findings on determinants.

A third gap concerns the joint action of indicators. Determinants have generally been entered as separate additive terms, which assumes that the effect of each indicator does not depend on the level of the others. The interest rate and the economic conditions of trading partners both move with the business cycle, and the effect of one may change with the level of the other. An additive model absorbs such a change into the separate coefficients and cannot show it.

The present study addresses the three gaps. First, it applies one set of candidate variables and one selection procedure to Busan Port, Incheon Port, and Gwangyang Port, so that differences in the estimates follow from the ports rather than from the models. The comparison links the direction of each response to the cargo each port handles and shows what the combined total hides. Second, the variables selected in the regression enter the forecasting models by name as exogenous regressors. The same inputs are used in the statistical and the deep learning models, so the forecasting stage can be read against the findings on

determinants. Third, interaction and squared terms are added to test whether the effect of the interest rate depends on Chinese growth. The test is carried out on the combined total of the three ports, and its result sets the axes of the scenarios from which port strategies are drawn.

3. METHODS

The analysis follows four steps. Each step produces an output that feeds the next step. Figure 1 shows the overall procedure. The first step identifies the factors that affect throughput at each port. Multiple linear regression is applied. The second step builds time series forecasting models. Variables found significant in the first step enter as exogenous regressors, and forecast errors are compared across models and across ports. The third step examines relationships among the main variables. Interaction and squared terms are added to capture effects that a linear additive form cannot express. The fourth step brings the results together through SWOT analysis. Scenarios are set along the variables that showed a significant interaction in the third step, and response directions are proposed for each port type. A dashed feedback path runs from the third step back to the first, indicating that structural effects found in the third step are reflected in a respecified regression model.

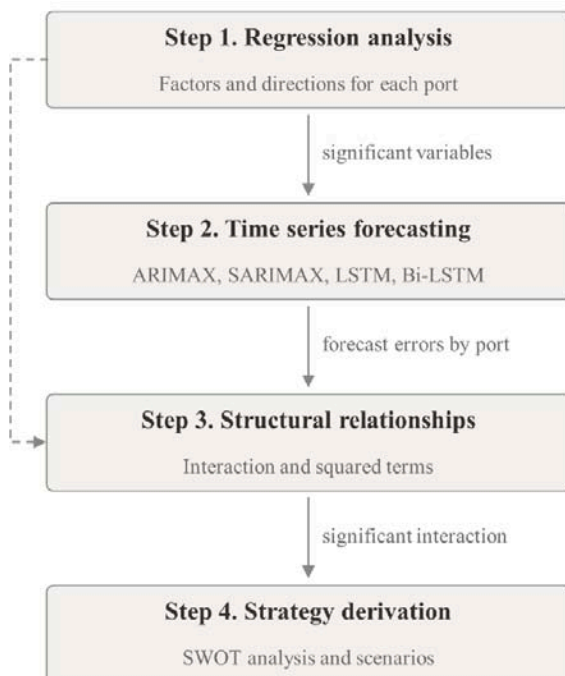


Figure 1: Research framework.

3.1. Study Scope, Data Sources, and Variable Selection

This study covers 120 monthly observations from January 2013 to December 2022. Container throughput data come from the Korean Statistical Information

Service (KOSIS). Busan Port, Incheon Port, and Gwangyang Port were selected from the ports listed in the database. A total throughput variable was created by adding the three ports together. Throughput is measured in TEU, which stands for twenty-foot equivalent unit and represents one twenty-foot container.

Throughput at each port was measured as the total of gateway cargo, comprising imports and exports, and transshipment cargo. Facilities and staff at a port serve both types together, so operating decisions rest on the total rather than on either type alone. The three ports differ in cargo mix as well as in scale. Transshipment accounted for 56.7% of throughput at Busan Port in 2025, compared with 12.1% at Gwangyang Port and 1.1% at Incheon Port [7]. Busan Port handles a large volume of cargo that transfers between vessels bound for third countries. Throughput at Busan depends heavily on the port call networks of shipping lines. Incheon Port serves the metropolitan market around Seoul and handles mostly gateway cargo. Consumer goods and refrigerated cargo account for a relatively high share there. Gwangyang Port sits next to steel and petrochemical complexes. Throughput at Gwangyang moves with the raw material demand and product exports of nearby industries. A difference in cargo mix means a difference in where demand starts. Transshipment cargo arrives through the route decisions of shipping lines. Gateway cargo arises directly from the trade activity of shippers. This study examines whether the difference appears as a difference in response to macroeconomic indicators. The total throughput of the three ports rose gradually over the study period, and swings widened after 2020.

Independent variables were selected from the five factor groups identified in prior work. Table 1 presents each variable with its unit, geographic coverage, source, frequency, and definition. The macroeconomic group covers gross domestic product, economic growth rate, and consumer price index. The monetary and financial group covers the base interest rate, the KRW-USD exchange rate, and foreign direct investment. The shipping market group covers crude oil prices, the Baltic Dry Index (BDI), and the Shanghai Containerized Freight Index (SCFI). The logistics group covers the Logistics Performance Index and foreign trade dependency. The geopolitical group covers the Geopolitical Risk Index. Gross domestic product, economic growth rate, foreign trade dependency, and the Logistics Performance Index are available by country. Trade statistics from the Korea Trade-Investment Promotion Agency identify China, the United States, Vietnam, Hong Kong, and Japan as the top export destinations. These four indicators were collected for six countries including Korea.

Table 1: Variables Description

Variable	Unit	Coverage	Data source	Frequency	Description
PUS_all	TEU	Korea	KOSIS	Monthly	Monthly container throughput handled at Busan Port
INC_all	TEU	Korea	KOSIS	Monthly	Monthly container throughput handled at Incheon Port
KAN_all	TEU	Korea	KOSIS	Monthly	Monthly container throughput handled at Gwangyang Port
TOT_all	TEU	Korea	-	Monthly	Sum of container throughput at the three ports
GPR	Index (1985–2019 avg. = 100)	Global	matteoiacoviello.com	Monthly	Share of articles on adverse geopolitical events in major newspapers of the United States, the United Kingdom, and Canada
CPI	Index (2020 = 100)	Korea	KOSIS	Monthly	Change in the prices of goods and services bought by consumers, with 2020 as the base year
GOP	USD/barrel	Global	NYMEX	Daily	Price of West Texas Intermediate crude oil
BDI	Index	Global	Baltic Exchange	Daily	Freight rate level in the global dry bulk market, published daily by the Baltic Exchange
SCFI	Index	Global	Shanghai Shipping Exchange Institute	Weekly	Container freight rate level on 15 routes departing Shanghai, published weekly by the Shanghai Shipping Exchange
IR_kor	%	Korea	Bank of Korea	Monthly	Base rate set by the Bank of Korea
FX	KRW/USD	Korea	Bank of Korea	Daily	Price of one US dollar in Korean won
LPI	Score (1–5, higher = better)	6 countries	World Bank	Biennial	Score covering customs, infrastructure, logistics services, and timeliness, published every two years by the World Bank
GDP	USD (billions)	6 countries	IMF	Annual	Total value of goods and services produced in each country
FDI	USD (thousands)	Korea	KOSIS	Annual	Outflow of capital from Korean investors seeking a lasting management interest in foreign firms
EGR	%	6 countries	KOSIS	Annual	Year-on-year percentage change in GDP
TD	%	6 countries	KOSIS	Annual	Ratio of exports plus imports to GDP

Notes: Coverage indicates the geographic scope of each variable. Variables marked as six countries were collected for the Republic of Korea, China, the United States, Japan, Hong Kong, and Vietnam. TEU stands for twenty-foot equivalent unit. For index variables, the period shown in parentheses is the base period whose value is set to 100. BDI and SCFI track freight rates for dry bulk and container shipping, respectively. Daily series take the closing value of each month. Annual series take the same value in every month of the year. The Logistics Performance Index was linearly interpolated between publication years and held constant within each year. The weekly SCFI was converted to monthly values by averaging the weekly observations within each month.

The Geopolitical Risk Index was developed by Caldara and Iacoviello [25]. The index counts articles on geopolitical events in major newspapers published in the United States, the United Kingdom, and Canada. The index was built outside Asia and has limits in reflecting conditions in the region. It remains the most widely used measure of geopolitical risk. The World Bank publishes the Logistics Performance Index every two years. Missing years were filled by linear interpolation. Interpolation keeps the series continuous but estimates values that were not observed. Table 2 presents descriptive statistics for each variable.

3.2. Multiple Linear Regression for Factor Identification

Multiple linear regression was applied to identify the factors that affect throughput. The dependent variables are monthly container throughput at Busan Port, Incheon Port, and Gwangyang Port, together with the

sum of the three. A separate model was estimated for each dependent variable. The same candidate variable set and the same selection procedure were applied to all four models. This study compares response structures across ports. Different variable sets would make it impossible to tell whether a difference in coefficients comes from model specification or from the port itself.

Multicollinearity among independent variables lowers the accuracy of coefficient estimates. It can also distort the sign and size of the coefficients. The variance inflation factor was calculated for each independent variable. Equation (1) gives the formula.

$$VIF_j = \frac{1}{1-R_j^2} \quad (1)$$

R_j^2 is the coefficient of determination obtained by regressing the j th independent variable on the remaining independent variables. A value above 10

Table 2: Descriptive Statistics

Variable	Mean	SD	Min	Max
PUS_all	1,716,361	155,924	1,296,213	2,016,797
INC_all	237,378	40,889	136,449	310,355
KAN_all	185,950	18,870	131,908	224,700
TOT_all	2,139,689	191,572	1,594,641	2,488,011
GPR	100.18	32.13	58.42	318.95
CPI	98.43	4.22	92.71	109.26
GOP	65.66	22.15	18.84	114.67
BDI	1,341	784	317	5,167
SCFI	1,446	1,215	414	5,067
IR_kor	1.58	0.67	0.50	3.25
FX	1,144.44	71.83	1,011.50	1,439.96
LPI_chn	3.61	0.09	3.46	3.76
LPI_hkg	3.94	0.05	3.81	4.00
LPI_jpn	4.03	0.06	3.93	4.10
LPI_kor	3.67	0.04	3.59	3.76
LPI_usa	3.93	0.05	3.87	4.01
LPI_vnm	3.16	0.18	2.88	3.40
GDP_chn	13,340.77	2,752.02	9,624.93	17,848.54
GDP_hkg	333.61	30.99	275.70	368.95
GDP_jpn	4,899.43	289.87	4,256.41	5,212.33
GDP_kor	1,595.74	129.58	1,370.63	1,818.43
GDP_usa	20,403.98	2,621.31	16,880.68	25,744.10
GDP_vnm	297.23	62.13	212.73	407.97
FDI	50,468,697	17,470,557	28,725,372	77,167,060
EGR_chn	6.20	1.92	2.20	8.40
EGR_hkg	1.20	3.67	-6.50	6.40
EGR_jpn	0.50	1.78	-4.30	2.10
EGR_kor	2.70	1.23	-0.70	4.30
EGR_usa	2.10	1.99	-2.80	5.90
EGR_vnm	6.10	1.79	2.60	8.00
TD_chn	35.26	3.73	31.70	43.46
TD_hkg	350.57	32.22	306.47	419.96
TD_jpn	29.38	3.66	25.04	38.86
TD_kor	68.60	7.69	59.59	84.56
TD_usa	18.61	1.50	18.20	23.21
TD_vnm	150.51	18.76	123.56	182.31

Notes: Container throughput, foreign direct investment, BDI, and SCFI are reported as integers. All other variables are reported to two decimal places. Country suffixes chn, hkg, jpn, kor, usa, and vnm denote China, Hong Kong, Japan, the Republic of Korea, the United States, and Vietnam, respectively.

indicates serious multicollinearity [40]. Variables above this threshold were removed one at a time, starting with the highest value. The factor was recalculated after each removal. The final model includes only variables that met the threshold. Every retained coefficient reached significance at the 0.05 level, except the SCFI in the combined total model, which reached the 0.10 level. Standard errors, t statistics, and p values were used to assess the significance of each coefficient. Comparison across ports is based on the sign and the

significance of each coefficient rather than on its magnitude, since throughput levels differ widely across the three ports.

3.3. Time Series Forecasting with Exogenous Variables

Four forecasting models were applied in this study. Two are traditional statistical models, ARIMAX and SARIMAX. Two are deep learning models, LSTM and Bi-LSTM. Prior work shows that the relative

performance of the two streams depends on the scale and volatility of the data. No stream was chosen in advance, and the four models were built in parallel for comparison. Variables found significant in the regression analysis were entered as exogenous regressors in all four models. This design carries the result of the factor analysis into the forecasting stage. The set of exogenous variables differs by port, and each port uses the variables found significant in its own regression model.

ARIMAX adds an exogenous term to the autoregressive integrated moving average model. The model reflects the influence of external indicators alongside the autoregressive and moving average structure of the series itself. SARIMAX extends ARIMAX with a seasonal component. The model is written with non-seasonal orders (p, d, q) and seasonal orders $(P, D, Q)_s$. Port throughput contains annual cycles caused by holidays and peak seasons. Both models were built to see how the explicit treatment of seasonality affects forecast performance. Equation (2) gives the general form of SARIMAX.

$$\phi_p(B^s)\phi_p(B)(1-B^s)^D(1-B)^d y_t = \theta_q(B^s)\theta_q(B)\varepsilon_t + \sum_{i=1}^m \beta_i x_{i,t} \quad (2)$$

$\phi_p(B)$ and $\phi_p(B^s)$ are the non-seasonal and seasonal autoregressive polynomials. $\theta_q(B)$ and $\theta_q(B^s)$ are the non-seasonal and seasonal moving average polynomials. B is the backshift operator and s is the seasonal period. ε_t is white noise. $x_{i,t}$ and β_i are the i th exogenous variable and its coefficient. Removing the seasonal terms gives the ARIMAX model.

LSTM was proposed to address the vanishing gradient problem of recurrent neural networks [41]. The model carries a cell state that stores long-term information and a hidden state that passes short-term information to the next time step. Three gates control the flow of information into and out of the cell state. Each gate applies a sigmoid function and returns a value between 0 and 1. A value near 0 blocks information and a value near 1 lets it pass. The forget gate decides how much of the previous cell state to keep.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3)$$

The input gate decides how much new information to add, and a candidate cell state holds that new information.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (5)$$

The cell state is then updated from the two gates.

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (6)$$

The output gate decides how much of the cell state passes to the hidden state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (7)$$

$$h_t = o_t \odot \tanh(C_t) \quad (8)$$

Here x_t is the input at time t and h_{t-1} is the hidden state at the previous step. W and b are weight matrices and bias vectors, σ is the sigmoid function, and $\odot$ denotes element-wise multiplication.

Bi-LSTM runs one LSTM forward through the input sequence and a second LSTM backward [42]. The forward layer reads the sequence from the first time point to the last, and the backward layer reads it in reverse.

$$\vec{h}_t = \text{LSTM}(x_t, \vec{h}_{t-1}), \tilde{h}_t = \text{LSTM}(x_t, \tilde{h}_{t+1}) \quad (9)$$

The hidden state at each time point joins the outputs of the two layers.

$$h_t = [\vec{h}_t; \tilde{h}_t] \quad (10)$$

Each time point therefore draws on earlier and later points within the input sequence.

The number of units and the batch size were tuned for each port. The number of layers, the learning rate, the number of epochs, the input sequence length, the optimizer, and the loss function were held constant across ports. LSTM used two layers, 300 epochs, and a sequence length of one month. Bi-LSTM used three layers, 400 epochs, and a sequence length of three months. Both models used a learning rate of 0.001, the Adam optimizer, and the mean squared error as the loss function. Table 3 presents the full configuration for each port.

The study period runs from January 2013 to December 2022, the period over which data for every variable could be collected at the time of the study. The 120 monthly observations were split at a ratio of seven to three. The 84 months from January 2013 to December 2019 were used for training, and the 36 months from January 2020 to December 2022 were used for testing. The test period contains the sharp swings caused by the COVID-19 pandemic. A sample of 120 observations is small for deep learning models. A model with many parameters can fit the training period closely and still perform poorly on new data. Every performance measure reported in this study was computed on the test period, which the models did not see during training, so any overfitting would appear as

Table 3: Model Configuration by Port

Model	Total	Busan	Incheon	Gwangyang
ARIMAX				
Order	(0,0,1)	(3,0,1)	(0,0,3)	(0,0,1)
SARIMAX				
Order	(0,0,1) (2,0,0) [6]	(0,0,1) (2,0,1) [12]	(0,0,1) (1,0,0) [6]	(0,0,1) (1,0,0) [12]
LSTM				
Layers	2	2	2	2
Learning rate	0.001	0.001	0.001	0.001
Epochs	300	300	300	300
Input sequence length	1	1	1	1
Optimizer	Adam	Adam	Adam	Adam
Loss function	MSE	MSE	MSE	MSE
Units	256	256	64	256
Batch size	16	16	16	8
Bi-LSTM				
Layers	3	3	3	3
Learning rate	0.001	0.001	0.001	0.001
Epochs	400	400	400	400
Input sequence length	3	3	3	3
Optimizer	Adam	Adam	Adam	Adam
Loss function	MSE	MSE	MSE	MSE
Units	192	192	192	192
Batch size	32	32	32	32

Notes: MSE denotes mean squared error.

higher test error. The same split was applied to all four models, so the comparison rests on identical data.

Forecast performance was measured by RMSE and MAPE. RMSE carries the same unit as the dependent variable and gives greater weight to large errors. MAPE expresses relative error as a percentage and allows comparison across series of different scale. The two measures capture different aspects, so both were used. Both measures were computed once over the full 36-month test period for each model and port.

Throughput levels differ widely across the four dependent variables. RMSE alone therefore does not support comparison across ports. Each value was divided by the monthly average throughput of the port to obtain a relative error. Comparison of forecast performance across ports is based on the relative error.

3.4. Interaction and Nonlinear Effects Among Variables

The regression analysis treats each variable as acting independently and in linear form. Some effects cannot be expressed in this form. The interest rate and the economic growth rate of a trading partner both

move with the business cycle, and the effect of one may depend on the level of the other. A variable may also relate to throughput in a nonlinear way.

Interaction and nonlinear effects among the main variables were examined for the combined total of the three ports. Variables found significant in the regression analysis were used, together with the exchange rate. Prior work identifies the exchange rate as a determinant of import and export volumes, so the variable was retained for this stage. All variables were standardized to a mean of 0 and a standard deviation of 1 before estimation. Standardization removes the effect of different measurement scales and allows the relative size of coefficients to be compared. Two additional terms were included. An interaction term is the product of two variables. A significant coefficient on the interaction term means that the effect of one variable changes with the level of the other. A squared term captures a nonlinear relationship. A negative coefficient on the squared term indicates an inverted U shape, and a positive coefficient indicates a U shape. The significance of each coefficient was assessed by a z test. Equation (11) gives the statistic.

$$z = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \quad (11)$$

$\hat{\gamma}$ is the estimated coefficient and $SE(\hat{\gamma})$ is its standard error. The statistic follows a standard normal distribution. A value above 1.96 in absolute terms indicates significance at the 0.05 level, and a value above 2.58 indicates significance at the 0.01 level.

3.5. Strategy Derivation Through SWOT Analysis and Scenarios

SWOT analysis was used to connect the quantitative results of the regression, forecasting, and interaction analyses to port management strategies. SWOT analysis separates internal strengths and weaknesses from external opportunities and threats. Weihrich extended the framework into the TOWS matrix, which derives strategies from combinations of these elements [43]. Each SWOT element in this study was drawn from the analytical results rather than set at will. Strengths and weaknesses come from the structural features of Korean ports identified in the analysis. Opportunities and threats come from the possible future movement of the external indicators used in the analysis. The finding that response structures differ by port was classified as a strength, since it allows tailored strategies for each port. The finding that all significant factors are external indicators beyond port control was classified as a weakness.

External factors identified through SWOT analysis do not by themselves specify when or how to respond. Scenarios were therefore set along combinations of

levels of the main external indicators, and response directions were proposed for each port type under each scenario. The axes of the scenarios were chosen from the variable combination that showed a significant interaction in the structural analysis. A significant interaction means that the effect of one variable changes with the level of the other. The combined effect of the two variables therefore differs from the sum of their individual effects. Variables without a significant interaction would produce scenarios whose outcomes are simply the sum of individual effects, which offers little basis for separating one scenario from another.

The two selected variables were divided into high and low levels, which produced four scenarios in a two-by-two design. The expected direction of throughput changes and the response direction for each port were derived for each scenario. Response directions were set from the cargo mix of each port and the response structures found in the regression analysis.

4. RESULTS AND DISCUSSION

4.1. Factors Affecting Throughput by Port

Table 4 presents the results for the four regression models. Variables from all five factor groups entered the candidate set. Those exceeding a variance inflation factor of 10 were removed one at a time, and the factor was recalculated after each removal. The highest value in the final models was 9.28, so no serious

Table 4: Regression Results for Monthly Container Throughput

Variable	Coefficient	S.E.	t-value	p-value	VIF
Combined total model (TOT_all)					
Constant	1,041,000.00	138,000.00	7.54	<0.001	-
IR_kor	-62,540.00	17,900.00	-3.49	<0.001	5.25
EGR_chn	-8,263.78	884.45	-9.34	<0.001	9.28
SCFI	-32.45	17.11	-1.90	0.060	3.33
Busan Port model (PUS_all)					
Constant	467,100.00	87,500.00	5.34	<0.001	-
IR_kor	-13,610.00	4,689.51	-2.90	0.004	1.13
EGR_chn	-3,655.18	271.61	-13.46	<0.001	2.62
SCFI	-25.74	6.91	-3.73	<0.001	2.74
Incheon Port model (INC_all)					
Constant	57,680.00	23,000.00	2.51	0.014	-
IR_kor	-2,059.39	168.55	-12.22	<0.001	3.00
EGR_chn	-4,134.98	1,272.94	-3.25	0.002	1.13
SCFI	-8.77	2.64	-3.32	<0.001	3.11
Gwangyang Port model (KAN_all)					
Constant	327,100.00	23,600.00	13.84	<0.001	-
EGR_chn	118.62	21.10	5.62	<0.001	2.51
SCFI	3.70	1.25	2.97	0.004	2.53

multicollinearity remains. The final models retain the base interest rate, the economic growth rate of China, and the SCFI. The other indicators did not survive the selection, including the Baltic Dry Index, the exchange rate, the consumer price index, gross domestic product, foreign direct investment, the Logistics Performance Index, foreign trade dependency, and the Geopolitical Risk Index.

Busan Port and Incheon Port share one pattern. The base interest rate, the economic growth rate of China, and the SCFI all carry negative coefficients, and every coefficient reaches significance at the 0.05 level or better. A rise in the base interest rate raises the cost of corporate funding and reduces liquidity in the market. Economic activity slows, and trade volume falls with it. A rise in the economic growth rate of China strengthens the ports of that country, and cargo that might otherwise move through Korean ports can be handled there instead. A rise in the SCFI raises the cost of moving a container, which weighs on the volume of trade that passes through both ports. Gwangyang Port shows a different pattern. The economic growth rate of China and the SCFI both carry positive coefficients, and both reach significance at the 0.01 level or better. The two variables therefore act on Gwangyang Port in the direction opposite to that observed at Busan Port and Incheon Port. The base interest rate did not remain in the final model for this port.

The reversal at Gwangyang Port matches the cargo the port handles. Busan Port depends on transshipment cargo that shipping lines route through Korea, and growth in a trading partner draws that cargo toward the ports of the partner. Incheon Port serves the consumer market of the metropolitan area, and growth in a trading partner strengthens the producers and the ports of that partner in the same way. Gwangyang Port handles cargo tied to the steel and petrochemical complexes in its hinterland. Growth in a trading partner raises direct trade with those industries, and throughput rises with it. The direction of the relationship therefore depends on whether a port serves transfer traffic, consumer demand, or industrial demand. The coefficients describe associations over the study period. Throughput at Busan Port and Incheon Port rose over

the period while throughput at Gwangyang Port declined, so part of the difference in sign may reflect these long-run trends. The model for the combined total carries negative coefficients on all three variables. Busan Port accounts for about 80% of the combined volume, so the aggregate follows the pattern of that port and the reversal at Gwangyang Port does not appear.

4.2. Forecasting Performance Across Models and Ports

Each model was trained on the 84 months from January 2013 to December 2019 and tested on the 36 months from January 2020 to December 2022. Table 5 shows forecasting performance for the four models, and Figures 2 to 5 show the actual and fitted series for total throughput, Busan Port, Incheon Port, and Gwangyang Port. LSTM produced the lowest MAPE and the lowest RMSE at every port. Bi-LSTM ranked second at every port on both measures.

The two statistical models produce a smooth path through the test period. The actual series swings from month to month, and neither ARIMAX nor SARIMAX reproduces the size of those swings. The direction of the error also varies by port. ARIMAX runs above the actual series at the combined total and at Busan Port, and below it at Incheon Port. SARIMAX drops sharply at the start of the test period and recovers slowly. The test period covers the COVID-19 pandemic, and no comparable episode appears in the training period. LSTM and Bi-LSTM track the month-to-month movement at every port. The contrast points to the capacity of deep learning models to learn patterns that a linear form cannot express. Bi-LSTM carries more parameters than LSTM and reads each series in both directions. The added capacity did not lower the error at any of the four dependent variables. LSTM produced the lower error in every case. The gap was widest for total throughput in RMSE terms and for Gwangyang Port in MAPE terms.

Throughput levels differ across the four dependent variables, so RMSE was divided by the mean monthly throughput of each series. The relative error of LSTM was 5.49% for total throughput, 5.91% for Busan Port,

Table 5: Forecasting Performance by Model and Port

Model	Total		Busan		Incheon		Gwangyang	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
ARIMAX	6.56%	222,215.94	6.56%	191,888.25	9.14%	30,631.08	9.85%	21,373.70
SARIMAX	6.50%	177,082.88	6.69%	124,169.03	8.60%	28,133.00	10.94%	20,962.72
LSTM	3.94%	117,519.15	4.67%	101,458.51	7.91%	23,898.15	7.83%	15,421.90
Bi-LSTM	4.72%	149,981.89	5.02%	110,172.51	8.18%	26,892.96	8.73%	17,611.37

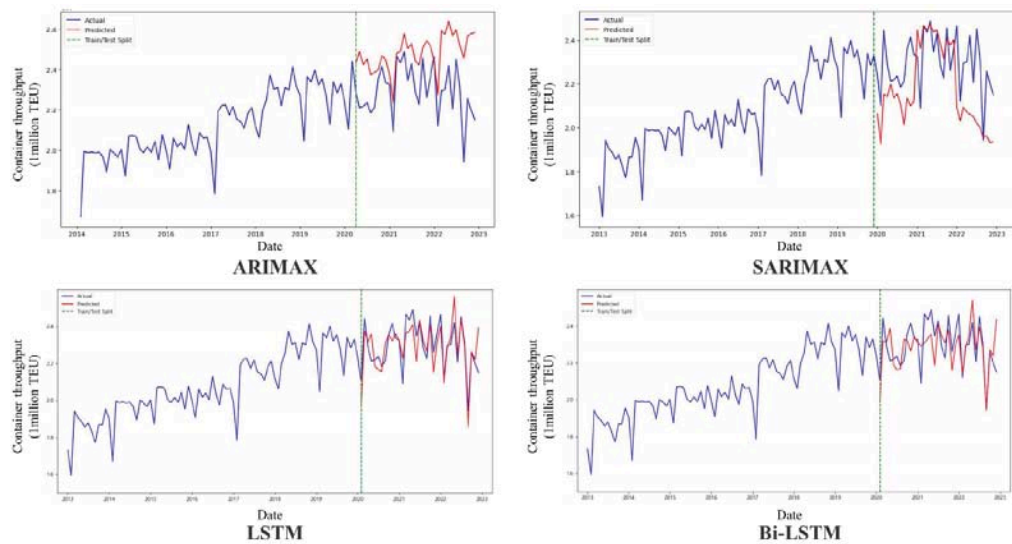


Figure 2: Observed and predicted container throughput for the three ports combined, from the four forecasting models. The dashed vertical line separates the training period (January 2013 to December 2019) from the test period (January 2020 to December 2022).

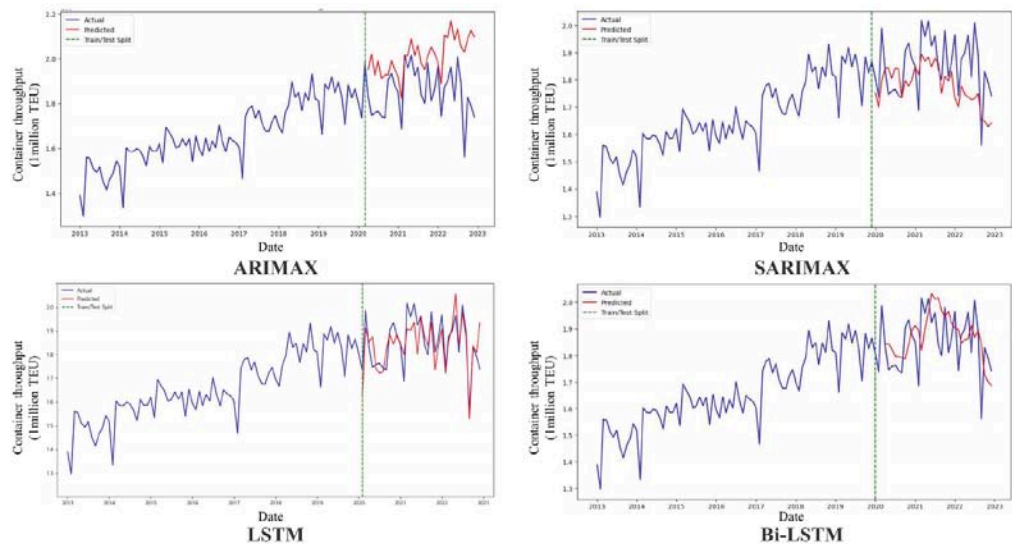


Figure 3: Observed and predicted container throughput at Busan Port, from the four forecasting models. The dashed vertical line separates the training period (January 2013 to December 2019) from the test period (January 2020 to December 2022).

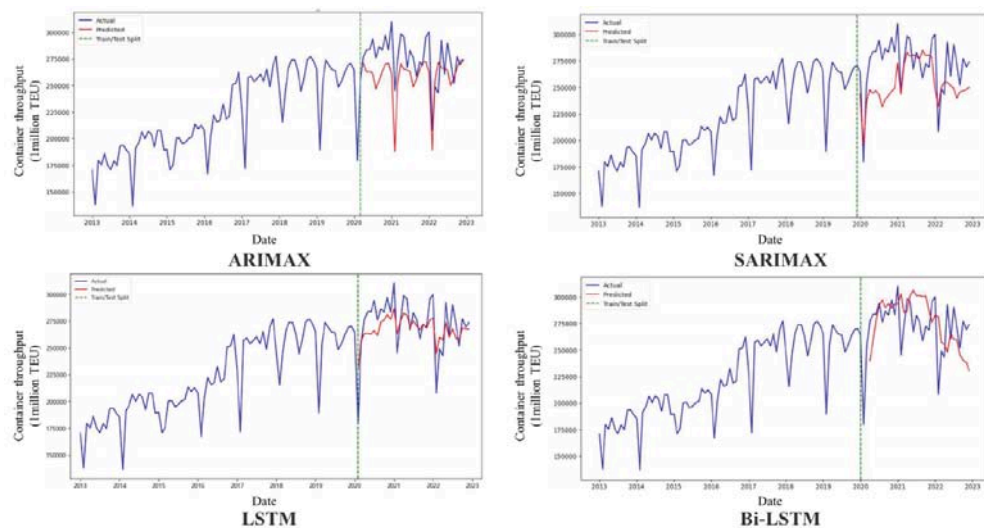


Figure 4: Observed and predicted container throughput at Incheon Port, from the four forecasting models. The dashed vertical line separates the training period (January 2013 to December 2019) from the test period (January 2020 to December 2022).

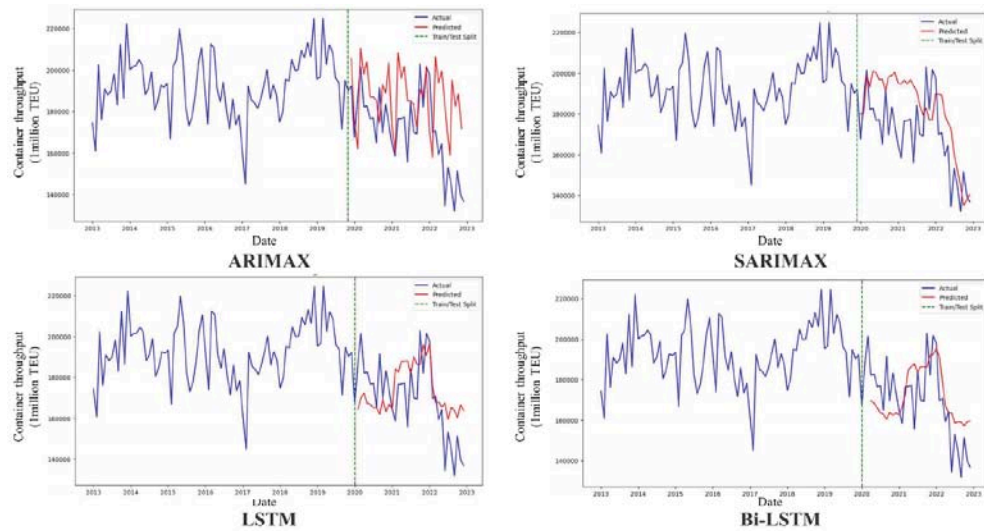


Figure 5: Observed and predicted container throughput at Gwangyang Port, from the four forecasting models. The dashed vertical line separates the training period (January 2013 to December 2019) from the test period (January 2020 to December 2022).

10.07% for Incheon Port, and 8.29% for Gwangyang Port. Incheon Port and Gwangyang Port carry higher relative error than Busan Port under every model. The two smaller ports also vary more from month to month. The standard deviation of monthly throughput is 17.2% of the mean at Incheon Port and 10.1% at Gwangyang Port, against 9.1% at Busan Port.

4.3. Interaction and Nonlinear Effects on Total Throughput

Table 6 presents the estimates from the model that adds interaction and nonlinear terms to the main effects. The model was fitted on the combined total of the three ports. All variables were standardized before estimation, so each coefficient shows the change in throughput in standard deviations when the variable moves by one standard deviation. The model carries the base interest rate, the economic growth rate of China, the SCFI, and the exchange rate as main effects, together with the product of the interest rate and Chinese growth and the square of Chinese growth. The variable set therefore differs from the one behind Table 4, and coefficients from the two tables are not directly comparable. Every coefficient in the model reached significance at the 0.001 level. Among the

main effects, the economic growth rate of China, the base interest rate, and the exchange rate carry negative coefficients, while the SCFI carries a positive coefficient. The interaction term and the squared term also reached significance, and the two terms carry the findings of this section.

The squared term for the economic growth rate of China carries a negative coefficient, so the relationship between Chinese growth and Korean port throughput does not follow a straight line. The effect of Chinese growth becomes more negative as growth rises. A model that assumes a constant effect would therefore understate the response at high growth and overstate it at low growth. Chinese growth ranged from 2.20% to 8.40% over the study period, and the reading holds within that range.

The interaction term is the product of the base interest rate and the economic growth rate of China, and it carries a negative coefficient. The effect of one variable therefore depends on the level of the other. A rise in the interest rate weighs on throughput more heavily when Chinese growth is high than when it is low, and the same holds when the two variables are read in the other order. Figure 6 shows the pattern.

Table 6: Interaction and Nonlinear Effects on Total Throughput

Variable	Standardized coefficient	Standard error	p
EGR_chn	-0.935	0.089	< 0.001
IR_kor	-0.506	0.068	< 0.001
SCFI	0.474	0.052	< 0.001
FX	-0.377	0.081	< 0.001
IR_kor × EGR_chn	-0.380	0.059	< 0.001
(EGR_chn) ²	-0.298	0.073	< 0.001

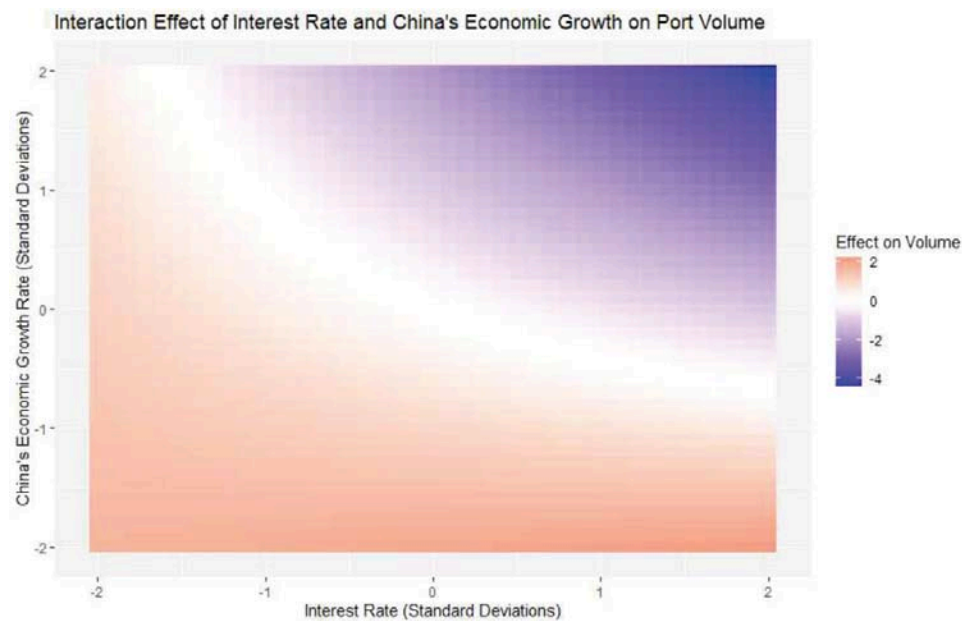


Figure 6: Interaction effect of the base interest rate and the economic growth rate of China on total container throughput.

Throughput falls most when both the interest rate and Chinese growth are high, and holds up best when both are low. The combination of the two indicators carries information that neither indicator carries alone. The estimates come from the combined total of the three ports, so they describe the aggregate response and not the response of any single port.

4.4. SWOT Analysis of Korean Port Conditions

The regression, forecasting, and interaction results describe how Korean ports respond to economic conditions, and those findings need to be organized before they can guide operating decisions. Figure 7 presents a SWOT analysis built on the findings. Strengths and weaknesses cover what the analysis reveals about the ports themselves. Opportunities and threats cover the external conditions the ports face.

Two strengths emerge. The first is that the three ports do not move together. Busan Port and Incheon Port respond negatively to the economic growth rate of China while Gwangyang Port responds positively. A condition that reduces throughput at one port can raise it at another, so the national portfolio is not exposed to a single direction of risk. The second is that the response to economic conditions is traceable to combinations of indicators rather than to indicators taken one at a time. The interest rate and Chinese growth act together with a significant negative interaction in the combined total, and knowing the combination gives a firmer basis for national planning than either indicator alone.

Two weaknesses emerge. The first is that every variable remaining in the final models is set outside the port. The base interest rate, the economic growth rate

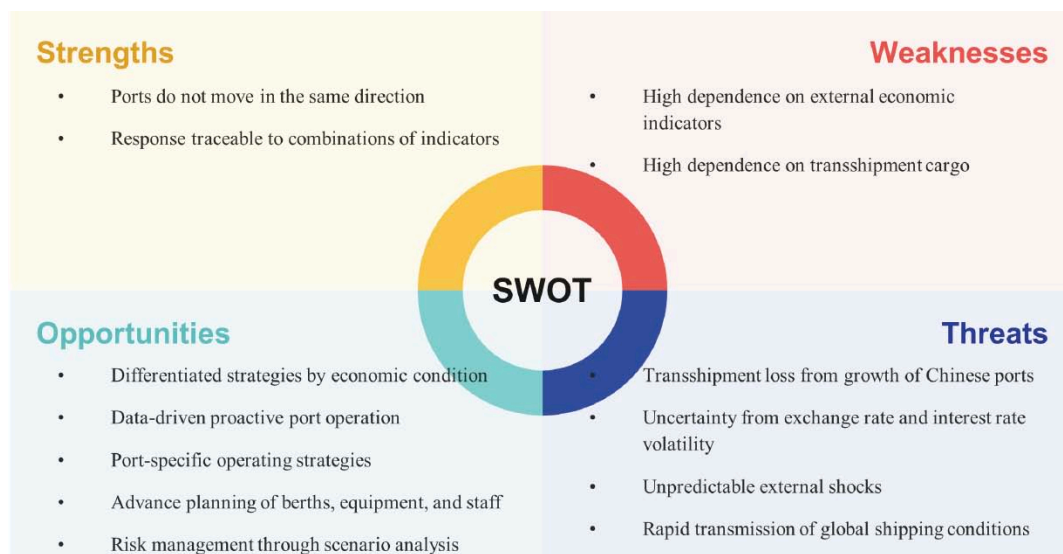


Figure 7: SWOT analysis of Korean port conditions based on the analytical results.

Table 7: Strategic Direction by Port

Port	Strategic direction
Busan Port	Diversify the transshipment portfolio
	Strengthen direct routes to North America
	Monitor the SCFI
	Attract high-value cargo
Incheon Port	Concentrate on gateway cargo for the metropolitan market
	Diversify direct routes to China
	Strengthen refrigerated cargo facilities
	Integrate services with metropolitan logistics parks
Gwangyang Port	Expand direct trade during periods of Chinese growth
	Expand container capacity for resin and chemical products
	Strengthen links with nearby industrial complexes
	Shorten handling time for containerized steel trade

of China, and the SCFI are all determined by conditions that no port authority can influence. Ports can prepare for movement in these indicators but cannot alter it. The second is the share of transshipment cargo at Busan Port, which handles more than half of its volume as transfer traffic. Cargo of that type responds to conditions in other countries rather than to domestic demand, and it can shift to another port without any change in Korean trade.

Opportunities follow from the same results. The interaction between the interest rate and Chinese growth in the combined total allows a national response to be prepared for each combination of the two indicators. Once response directions are known to differ by port, each port can pursue a strategy suited to the cargo it handles. Forecasting models give advance notice of the volume to expect, which supports planning of berth allocation, equipment deployment, and staffing. Monthly forecasts allow ports to act before conditions change rather than after. Scenario analysis prepares a response for each economic state in advance, which shortens the time between a change in conditions and a decision.

Four threats stand out. Chinese growth carried a negative coefficient at Busan Port, at Incheon Port, and in the combined model, so continued growth of Chinese ports draws transfer traffic away from Korea. Movement in exchange rates and interest rates raises uncertainty in trade volume, and both indicators lie outside port control. External shocks arrive without warning, and the two statistical models missed the movement that followed 2020 because no comparable episode appeared in the training period. The SCFI entered every port-level model as a significant variable, so conditions in world shipping reach Korean port throughput and leave little time to respond.

4.5. Scenario-Based Management Strategies by Port Type

The three ports respond to economic conditions in different directions, so a single strategy applied to all of them would work against its purpose at one port or another. Table 7 presents the strategic direction for each port, and Table 8 presents the strategies under each scenario.

Busan Port carries the highest share of transshipment cargo among the three ports. The negative coefficient on Chinese growth means that transfer traffic moves away as ports in China grow, and the share of that traffic makes the port sensitive to the shift. Busan Port needs to spread its transshipment portfolio across more origins. Direct routes to Southeast Asia, India, North America, and Europe reduce dependence on any single country. The SCFI also carried a significant coefficient for this port, so tracking the index gives an early reading of demand in world shipping.

Incheon Port handles almost all of its volume as gateway cargo for the metropolitan market, and it also responds negatively to Chinese growth. Growth in China strengthens producers and ports on the other side of the route the port depends on, which places its volume at risk. The concentration on a single market and a small set of routes leaves little room to absorb that shift. Spreading direct routes to China across more destinations reduces dependence on any single route. Consumer goods and refrigerated cargo already account for a high share at the port, and dedicated facilities for refrigerated cargo would build on a position that competing ports do not hold. Closer integration with logistics parks in the metropolitan area would strengthen the link between the port and the market it serves.

Table 8: Management Strategies under Four Economic Scenarios

Scenario	Condition	Combined total	National level	Busan Port	Incheon Port	Gwangyang Port
1	Low interest rate	Increase	Strengthen marketing	Attract transshipment cargo	Secure metropolitan cargo	Retain long-term contract shippers
	Low Chinese growth			Maximize berth utilization	Expand direct routes to China	Adjust utilization
2	High interest rate	Decrease	Operate labor flexibly	Focus on high-value cargo	Prioritize essential cargo	Expand capacity for resin and chemical containers
	High Chinese growth		Activate crisis response	Improve cost efficiency	Reduce operating costs	Strengthen links with industrial complexes
3	Low interest rate	Higher volatility	Allocate resources evenly	Diversify transshipment to Southeast Asia	Concentrate on metropolitan gateway cargo	Expand direct trade with China
	High Chinese growth		Continue long-term investment	Strengthen North American routes	Specialize in refrigerated cargo	Coordinate shipments with industrial complexes
4	High interest rate	Higher volatility	Reduce costs	Concentrate on core routes	Secure essential cargo	Lower utilization
	Low Chinese growth			Minimize operating costs	Maintain facilities	Reduce fixed costs

Notes: The combined total follows the model with interaction and squared terms, which was estimated for the combined total only. The direction at each port follows the signs in the port-level regression. Gwangyang Port responds positively to Chinese growth and did not retain the interest rate, so its volume falls in Scenarios 1 and 4 and rises in Scenarios 2 and 3.

Gwangyang Port responds positively to Chinese growth, in the direction opposite to the other two ports. The port handles cargo tied to the steel and petrochemical complexes in its hinterland, and growth in China raises direct trade with those industries. The port can capture that trade during periods of growth by expanding container handling capacity for the resin and chemical products those industries ship. Closer coordination with the complexes secures a base of cargo that does not depend on carrier routing decisions. The same link also works in reverse. A slowdown in China lowers direct trade, and the port carries little transfer traffic to offset the loss, so its exposure runs to a single trading partner rather than to a single carrier network. Working with steel producers on the flow between Korea and China would shorten handling time for the containerized share of that trade.

Four scenarios follow from the base interest rate and the economic growth rate of China, with each indicator read as high or low relative to its average over the study period. The two indicators were chosen because their interaction was significant in the model for the combined total. The expected change in the combined total follows that model. Low interest rates with low Chinese growth point to rising volume, high interest rates with high Chinese growth point to falling volume, and the two mixed scenarios point to higher variability. The interaction was estimated for the combined total only, so the direction at each port is

read from the signs in the port-level regression. Busan Port and Incheon Port carry negative coefficients on both indicators, so their direction under each scenario matches that of the combined total. Gwangyang Port responds only to Chinese growth, and in the positive direction. Its volume therefore falls in the first scenario and rises in the second, against the direction of the combined total. Table 8 sets out the response at the national level and at each port under each scenario.

5. CONCLUSION

Container throughput forecasts guide both facility investment and daily operation at ports, and the forecasts are difficult to build because throughput responds to conditions that ports do not control. This study examined how macroeconomic indicators affect container throughput at Busan Port, Incheon Port, and Gwangyang Port, using monthly data from January 2013 to December 2022. The same candidate variables and the same selection procedure were applied to every port, so that any difference in the estimates would follow from the ports rather than from the models. The analysis covered regression, time series forecasting, interaction and nonlinear effects, and the derivation of management strategies. The central finding is that the three ports do not respond to the same conditions in the same direction.

Regression analysis showed that the direction of the effect differs across ports. The base interest rate,

the economic growth rate of China, and the SCFI carried negative coefficients at Busan Port and Incheon Port. At Gwangyang Port both Chinese growth and the SCFI carried positive coefficients, and the interest rate did not remain in the final model. The reversal follows the cargo each port handles. Busan Port depends on transfer traffic and Incheon Port on consumer demand, and growth in a trading partner strengthens the producers and the ports on the other side of both routes. Gwangyang Port handles cargo tied to nearby steel and petrochemical complexes, so growth in a trading partner raises direct trade instead. The origin of demand therefore shapes the direction of the response. The model for the combined total carried negative coefficients throughout, so the reversal at Gwangyang Port disappears once the ports are added together.

Forecasting results showed that LSTM produced the lowest error at every port. The two statistical models produced a smooth path through the test period and did not reproduce the size of the month-to-month swings in the actual series. LSTM and Bi-LSTM tracked those swings, which points to the capacity of deep learning models to learn patterns that a linear form cannot express. Bi-LSTM carries more parameters than LSTM and reads each series in both directions, yet it did not lower the error at any of the four dependent variables. Relative error was higher at Incheon Port and Gwangyang Port than at Busan Port under every model, and the two smaller ports also varied more from month to month.

The model that added interaction and nonlinear terms showed that indicators do not act alone. The interaction between the base interest rate and Chinese growth was significant and negative, so throughput falls most when both indicators are high and holds up best when both are low. The squared term for Chinese growth was also significant, which means the negative effect strengthens as growth rises within the range observed over the study period. Single coefficients therefore do not capture the full response of throughput to economic conditions, and the combination of the two indicators became the basis for the four scenarios proposed here. These estimates come from the combined total of the three ports and describe the aggregate response rather than the response of any single port.

These findings carry practical value. Facility investment and operating plans are set port by port, and a national forecast cannot support those decisions when ports respond in opposite directions. A uniform national measure can work against its purpose at some ports. The four scenarios allow each port to prepare a response before conditions change, and the response differs by port because the exposure differs. Busan

Port and Incheon Port lose volume as a trading partner grows, so both need to spread their routes across more destinations. Gwangyang Port gains volume in the same conditions but loses it when that partner slows, so its exposure runs to a single trading partner rather than to a single carrier network. Forecasting models can also support short-term planning of berth allocation, equipment deployment, and staffing.

Several limits apply to the data and the models. The regression models were estimated in levels without formal tests for stationarity, autocorrelation, or heteroskedasticity, and the residuals show positive autocorrelation. The coefficients are therefore associations rather than causal effects. The 120 months of data form a small sample for deep learning and raise the risk of overfitting. The hyperparameters were set without a systematic search, so the reported performance may not represent the best accuracy these models can reach. The test period overlaps with the COVID-19 pandemic, so performance was measured under conditions that the training period did not contain. The models were compared on point measures of error over a single test period, and the differences between models were not tested for statistical significance. The exchange rate entered the models in nominal terms and therefore does not reflect changes in price levels between countries.

Further limits apply to the scope. Only three ports were examined, so the findings do not extend to every Korean port. Throughput was measured as the combined volume of import, export, and transshipment cargo, and the two kinds of cargo may respond to a given indicator in different directions. Analysis by cargo type would show which kind drives the reversal at Gwangyang Port. The independent variables are macroeconomic indicators that lie outside port control, and measures of port capability such as vessel waiting time, handling speed, or terminal automation were not included.

Future work can address these limits. Estimation that controls for long-run trends and corrects for serial correlation would show whether the differences between ports persist. A longer series would support deep learning models and allow the test period to cover more than one kind of shock. A systematic search over the hyperparameters would establish how far the deep learning models can be improved. A formal test of forecast accuracy such as the Diebold-Mariano test, applied over several rolling test windows, would show whether the differences between models are statistically meaningful. A real exchange rate adjusted by consumer price indices would separate price effects from currency effects. Port-level estimation of the interaction terms would show whether the

combinations that matter differ by port. Monthly data by cargo type are available for each port, and analysis at that level would test whether cargo composition drives the reversal found at Gwangyang Port. Adding measures of port capability such as waiting time or handling speed would identify factors that ports can act on directly, alongside the external factors examined here. A national figure does not tell a port manager what to expect, because the three ports move in different directions under the same conditions. Planning that starts from the port rather than from the national total is the more useful basis for decisions.

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AUTHOR CONTRIBUTIONS

Donghyeok Park: Conceptualization, Validation, Visualization, Writing - original draft, Writing - review & editing. Woowon Kim: Data curation, Formal analysis, Investigation, Methodology, Software, Writing - original draft. Donghee Oh: Validation, Writing - review & editing. Juneyoung Park: Supervision, Project administration, Funding acquisition, Writing - review & editing.

CONFLICT OF INTEREST

No conflict of interest.

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