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ORIGINAL ARTICLE

Forecasting throughput at a transshipment hub under trade dynamism and uncertainty in major production centers

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Abstract

The demand for port services is intricately tied to international trade between production centers and the global market. This paper introduces a unique econometric forecasting model tailored to predict container port throughput at a transshipment hub, leveraging the dynamic and uncertain nature of international trade flows, originating from three global production centers: China, the USA, and Germany. The paper examines how the trade flow dynamics of these centers impact a transshipment hub, especially in scenarios where the hub is strategically positioned along major shipping routes, serving as the sole container transshipment facility in a region. The validation of the model is conducted through empirical testing using time series analysis of trade flows from the above three major production centers to the South Asian port region. The Port of Colombo (PoC) is used as the regional hub port. The model incorporates external shocks to assess their influence on the demand for the services of the hub and its resilience to global disruptions. Findings indicate the substantial influence of China, with a notable impact on exports to the USA from South Asia and imports from Europe and Central Asia to China, establishing positive and long-term relationships with PoC. Furthermore, the paper offers insights into PoC's resilience during crises such as the Red Sea incident, leveraging its strategic location. The findings not only contribute in developing PoC's strategic position, but they also lay the groundwork for future studies on global trade patterns and the adaptability of transshipment hubs in the face of dynamic demand.

Keywords Transshipment port · International trade · Production centers · Uncertainty · Granger causality · VECM

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1 Introduction

Demand for seaport services depends on the structure of trade between a country and the rest of the world (Notteboom et al. 2022). Demand for transshipment services, however, depends not only on national demand but also on trade between third countries and major production centers. In maritime supply chains (MSC), shipping (links) and seaports (nodes) play a vital role in merchandise trade (Jiang et al. 2021). General cargo goods are typically transported in containers, and transshipment hubs facilitate their efficient handling in a relay network connecting production centers with demand points. Haralambides (2017) further mentions that containerships in deep-sea liner trades select only a few transshipment ports, which have become the foci of international trade in a hub-and-spoke network. The expansion of container terminal capacity, including its potential for transshipment, persists without interruption. This is a customary occurrence and, over time, port capacity aligns with the growth of international trade. Consequently, the capacities of transshipment ports must align with anticipated shifts in demand, accounting for the dynamic nature and volatility of international trade flows originating from major production centers. Of particular significance are the trade flows from such production centers to feeder market regions associated with transshipment ports within a hub-and-spoke network. Thus, the adaptability and scalability of transshipment hubs become paramount considerations to efficiently accommodate evolving trade patterns and meet the demands of global commerce. Figure 1 presents the link between production centers and demand points via transshipment hubs.

Figure 1 illustrates a transshipment hub port (THi) connected with shipping routes and international trade flows to and from the major production centers (PC1, PC2, PC3..Pi), regional markets (FN1, FN2, FN3,…Fi) in the proximity of TH, and its hinterland (LH). Demand for THi and its capacity requirements are determined by variations in trade flows originating from, and destined for, each production center and hinterland markets. Therefore, it is crucial to align the expansion of capacities and the number of transshipment hubs in the region with anticipated increases in trade volumes to ensure they can accommodate future international demand, which typically fluctuates with business cycles of economic growth, recessions, crises, and recoveries (UNCTAD 2022). Uncertainty in trade flows arises from both local circumstances and global developments such as the financial meltdown of 2008–2009 (Feng et al. 2019), the 2015 financial crisis in the USA (Strandenes & Thanopoulou 2020), and COVID-19 (Clarksons, 2023). According to World Trade Organization (2023) statistics, China is the leading exporter and importer, followed by the USA and Germany, as major world production centers. UNCTAD (2022) further mentions that intra-Asia routes, serving intra-regional supply chains, experienced the fastest growth from 2015 to 2022, mirroring global manufacturing trends. This growth was particularly notable between 2021 and 2022, with China acting as the global manufacturing center, supported by adjacent East Asian countries supplying various intermediate goods.

Transshipment ports play a critical role as strategic nodes in global supply chains. The management and operations of transshipment hubs have become

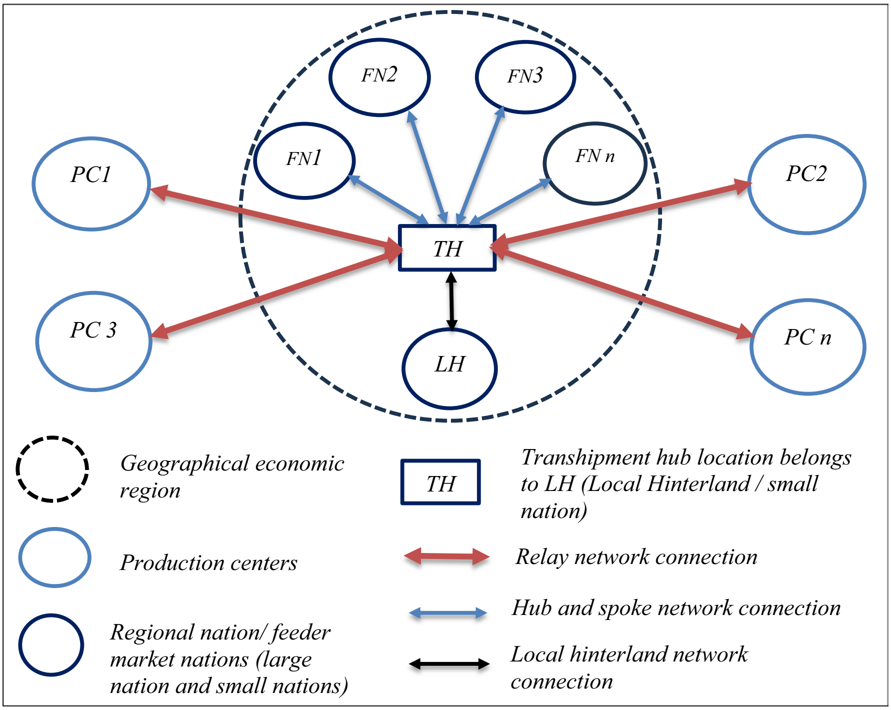

Fig. 1 Link between production centers and demand points via transshipment hubs. Source: The authors

increasingly complex due to growing trade volumes and carrier demands for port capacity and higher efficiency. Ports need to carefully plan their development and operations according to throughput forecasts. These become more challenging due to hinterland development and the consequent stochastic nature of the demand for port services (Cong et al. 2020; Munim et al. 2023; Dragan et al. 2021; Notteboom & Haralambides 2020; Du et al. 2019). Furthermore, Haralambides (2019) provides an extensive analysis of the impacts of increasing vessel sizes on port infrastructure and global logistics. This work is critical for understanding the challenges and opportunities that hub ports face in the context of international trade.

In view of the above, the main objective of this paper is to develop an econometric forecasting model for the container throughput of a transshipment hub port connected with shipping routes and international trade flows to and from major production centers and regional markets in the hub's vicinity. The model incorporates the trade dynamics of major production centers and global uncertainty. The paper is structured as follows: Sect. 2 presents a review of previous studies. The data and methodology are detailed in Sect. 3. Data analysis and their discussion are presented in Sect. 4, and the study concludes with policy implications along with future research directions in Sect. 5.

2 Literature review

Past research focusing on country level context has presented various port throughput forecasting models. Chou et al. (2008) developed an adjusted regression model for forecasting the volumes of import and export containers at ports in Taiwan using stepwise regression. Their model included containerized imports and exports as dependent variables and explanatory variables such as population, industrial production, gross national product (GNP), GNP per capita, wholesale price index, gross domestic product (GDP), agriculture GDP, industry GDP, and service GDP of Taiwan. The findings indicate that the modified regression model has superior predictive accuracy compared to other forecasting methods.

Tsai and Huang (2017) used GDP, exchange rates, economic growth, industry production index, per capita gross domestic production, and import and export trade value of Japan, Hong Kong, China, Taiwan, South Korea, and Singapore to develop artificial neural networks (ANNs) for predicting port throughput. The results indicated that prediction errors were relatively small, thus encouraging shipping companies to use their model in predictions of container flows.

The Vector Error Correction Model (VECM) developed by Gosasang et al. (2018) forecasted the port throughput of Laem Chabang Port using imported (inbound) and exported (outbound) containers, alongside variables such as economic growth rate, interest rates, inflation rate, fuel price, exchange rate, population, trade value of imports and exports, manufacturing production index (MPI), and industrial production index (IPI). The results entailed implications for port planning strategies related to capacity improvements in port terminals.

Rashed et al. (2018) developed an Autoregressive Distributed Lag (ARDL) model for ports in the Hamburg–Le Havre range using the volume of exports and imports, final household consumption, and total manufacturing output of the port's host country. Their results highlighted a long-term relationship between the trade indices of the EU19 and the overall container throughput, indicating a relatively high demand elasticity for port services.

Tang et al. (2019) presented multiple predictive models, including a gravity model, a triple exponential smoothing one, multiple linear regression, and a backpropagation neural network model, using data on total retail sales of consumer goods, GDP of the local city, import and export trade volumes, total output value of the manufacturing industry, and total fixed asset investment, to predict demand for Lianyungang Port and Shanghai Port. The comparison of model results showed that the backpropagation neural network model is more suitable in forecasting container throughput.

Cong et al. (2020) examined the impact of port throughput on port city economy using panel data from 16 ports with a Granger Causality test. Findings indicated that port throughput influences significantly Gross Domestic Product (GDP), although it has a negative effect on total retail sales of consumer goods (TRSCG). Port throughput showed synchronous growth with the added value of the secondary sector but exhibited a negative correlation with the primary and tertiary sectors. The causality test confirmed an interactive relationship between the economy of port cities and port throughput across the sampled city-port pairs.

Dragan et al. (2021) presented a dynamic factor analysis model—the Autoregressive Integrated Moving Average (ARIMAX) model—principal component regression, and Monte Carlo simulation, to forecast cargo throughput in the Adriatic seaport of Koper. The authors used data on liquid bulk, solid bulk cargo, general cargo, total cargo, containers, import, export, purchasing power parity, and GDP per capita. Their results indicated that a predictive system, due to its enhanced ability to forecast observed throughputs, can be regarded as a functional decision support system, and the proposed models surpass competing predictive models on port performance. Apart from using macroeconomic factors in forecasting models found in literature, several models exist to predict demand under uncertainty (Table 1).

Table 1 illustrates the array of uncertainties inherent in various predictive methodologies for demand forecasting in maritime contexts. Past research has predominantly concentrated on constructing predictive frameworks utilizing macroeconomic indicators and external perturbations for individual ports or clusters of ports within a region. However, previous studies have failed to model container throughput fluctuations, especially those related to connections between major production centers and hub ports, as well as inter-port trade dynamics within a port region. This represents a notable void in scholarly discourse, as there has been limited attention devoted to developing forecasting models tailored specifically for transshipment ports, particularly concerning the intricate trade dynamics associated with global production centers. This paper addresses this gap by introducing an econometric approach specifically tailored for transshipment hubs, incorporating trade dynamics stemming from the world's primary production centers.

3 Methods and model development

This section outlines the methodological approach employed in our study to investigate the shipping and trade dynamics between the major production centers and the regional markets. The methodology is structured to identify causality, test for stationarity, assess long-term equilibrium, and estimate the vector error correction model (VECM). Each stage leverages robust statistical techniques to ensure the reliability and validity of the results.

3.1 Stage 1: identification of causality

The Granger causality test was used to establish the usefulness of a variable in forecasting another, applied to identify pairwise causality between variables of time series data, of a high possibility for multicollinearity (Granger 1969). We use the Toda–Yamamoto (T–Y) approach of the Granger causality test which is superior to the traditional Granger causality test (Toda & Yamamoto 1995). T–Y eliminates the need for pre-testing for cointegration and it is suitable for any level of integration of the employed series and procedure of Granger causality test; it is moreover valid

Table 1 Methods and variables used to address uncertainty in port demand forecasts

Author(s)	Market/Port	Source of uncertainty and external shock	Methodology[a]	Variables
Li et al. (2018)	Tanker	2008–09 financial crisis	MF-CCA and MF-DPXA	Baltic Dirty Tanker Index (BDTI), Crude Oil Future Contracts
Strandenes and Thanopoulou (2020)	Bulk Cargo	US–China Trade frictions	Descriptive analysis	Income inequality dry bulk trades
Cullinane and Haralambides(2021)	Container	COVID-19	Descriptive analysis	Freight rates of various routes
Guo et al. 2021)	Port	Common uncertainty	Dynamic programming/SCIEI model	Draft, Volatility, scale parameter, interest rates, marginal operating cost, port throughput
Jiang et al. (2021)	Port/maritime supply chain	Common vulnerability	Fuzzy theory approach/PVA framework	Five key ports along an established MSC in China
Koyuncu et al. (2021)	container	COVID-19	SARIMA and ETS	Leibniz Institute for Economic Research (formerly Rheinisch-Westfälisches Institut)/ Institute of Shipping Economics and Logistics (RWI/ISL) Container Throughput Index
Nowińska and Schramm (2021)	Container	2008–09 financial crisis	Binary logit model	Vessel characteristics, freight rates, sales, origin of imports, crisis as a treatment variable
Zhao et al. (2022)	Container/ dry bulk	COVID-19	Exponential smoothing model	Baltic Dry Index (BDI), China Coastal Bulk Freight Index (CCBFI)
Gavalas et al. 2022)	Dry bulk, tanker, LPG	COVD-19	Correlation/regression/event study	Stock analysis from major shipping indexes (DJGSI, BDI, BDTI, BCTI, BLPG)

Table 1 (continued)

Author(s)	Market/Port	Source of uncertainty and external shock	Methodology[a]	Variables
Huang et al. (2022)	Container	COVID-19	Nonlinear programming Particle swarm optimization	Shipping hub-and-spoke network design, using Asia–Europe trade data
Michail and Melas (2022)	Tanker	COVID-19	Vector error correction	Specific route data, Baltic Clean Tanker index (BCTI), Baltic Dirty Tanker index (BDTI)
Choi et al. (2022)	Exports and imports	2008–09 financial crisis	Econometrics modeling	Cross-border trade credit liabilities, exports, imports, world GDP, real effective exchange rates
Chen et al. (2023b)	Dry Bulk and crude oil	COVID-19	Copula-VAR-BEKK-GARCH-X model	Baltic Dry Index, iron ore prices, and Brent crude oil prices
Chang et al. (2023)	Dry bulk market	COVID-19	Stepwise Regression	Baltic Dry Index, Brent, raw material prices, international commodity price volatility, etc
Baştuğ et al. (2023)	Container/liner shipping	Natural disaster, COVID-19, stakeholder relationships, cyber attacks	Spherical Fuzzy AHP	Questionnaire data on different shipping risks
Chen et al. (2023a)	Port congestion	COVID-19	Data mining/sliding window algorithm	AIS ship trajectory data for port time cost, port cost, congestion cost

[a]*MF-CCA* multi-factor canonical correlation analysis, *MF-DPXA* multi-factor dynamic panel X analysis, *SCIEI* stepwise capacity investment and exit integration, *PVA Framework* possibility-based value assessment, *SARIMA* seasonal autoregressive integrated moving average, *ETS* error, trend, seasonality, *VAR* vector autoregression, *BEKK-GARCH* Baba, Engle, Kraft, and Kroner-Generalized Autoregressive Conditional Heteroskedasticity

irrespective of whether the series is I (0), I (1), or I (2). If a time series, Y_t, can anticipate the future of another, X_t, then Y_t "Granger-causes" X_t. These two variables were considered with time period T, ($t = 1, 2, \ldots$ T) indicating their results at time t. A bivariate AR model can be written as shown in (1) and (2) to model X_t and Y_t (Granger 1969).

$$X_t = \beta_0 + \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{i=1}^{n} \beta_i X_{t-i} + e_{1t} \tag{1}$$

$$Y_t = \beta_1 + \sum_{i=1}^{n} \theta_i Y_{t-i} + \sum_{i=1}^{n} \delta_i X_{t-i} + e_{2t} \tag{2}$$

where β_0, β_1, α_i θ_i, β_i , and δ_i are parameters and e_t is the error term. Coefficients were estimated by Ordinary Least Squares. The F-statistic was used for the significance test. We tested for stationarity (below) and autocorrelation of the residuals (e_{1t} and e_{2t}).

3.2 Stage 2: testing for stationarity

As data on port demand are time series, stationarity is an important condition in regression analysis. We thus employed the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller 1979) and the Phillips–Perron (P–P) test (Phillips & Perron 1988) to test for stationarity and the results are shown in Tables 2 and 3.

Table 2 confirmed that series are not stationary at levels but they are at first differences (Table 3). Therefore, the series are I(1) integrated.

3.3 Stage 3: testing variables for long-term equilibrium

The Engle–Granger two-step procedure and the Vector Error Correction Model (VECM) were used (Engle & Granger 1987; Johansen & Juselius 1990). The estimation of the long-run relationships using Ordinary Least Squares (OLS) and the subsequent Error Correction Model (ECM) specification are commonly employed in cointegration analysis in maritime economics (Enders 2014). Diagnostic tests such as the Breusch–Godfrey test for autocorrelation and the Breusch–Pagan test for heteroskedasticity are standard procedures for validating ECMs in maritime-related research (Brooks 2014).

The long-run equilibrium relationship among the variables is estimated by Ordinary Least Squares (OLS). The regression equation is specified as

$$Y_t = \alpha + \beta X_t + \epsilon_t, \tag{3}$$

where Y_t is the dependent variable; X_t represents the set of explanatory variables, and ε_t denotes the error term. The residuals (ε_t) from the OLS regression were extracted and tested for stationarity using the ADF test. If the residuals are found to be stationary, then the variables are cointegrated.

Table 2 Results of ADF and PP tests for unit root in levels

Variables	ADF Fisher Chi-square			PP Fisher Chi-square		
	Individual intercept	Individual intercept and trend	None	Individual intercept	Individual intercept and trend	None
TEU	0.9599	0.5667	0.9993	0.9553	0.5079	0.9973
TMC	0.9995	0.8315	0.9999	0.9994	0.8027	0.9999
TMG	0.8406	0.3589	0.9608	0.8826	0.3934	0.9665
TUSA	0.9625	0.2485	0.9928	0.9984	0.2916	1.0000
SA to CN (M)	0.9023	0.6334	0.0027	0.8959	0.6383	0.8638
SA to CN (X)	0.9369	0.3144	0.9357	0.9369	0.5028	0.9046
SA to GE (M)	0.6181	0.9307	0.7093	0.6127	0.9032	0.6893
SA to GE (X)	0.7483	0.9460	0.9049	0.6059	0.4823	0.7680
SA to USA (M)	0.8173	0.2199	0.8038	0.8610	0.2686	0.8693
SA to USA(X)	0.9423	0.3226	0.9897	0.9672	0.4019	0.9929
CN to AF (M)	0.0319	0.3107	0.0065	0.7421	0.6151	0.659
CN to AF (X)	0.9843	0.5917	0.9939	0.9792	0.5917	0.9875
CN to EU and CA (M)	0.9740	0.2979	0.9932	0.9694	0.5285	0.9932
CN to EU and CA (X)	0.9717	0.4427	0.9930	0.9792	0.4397	0.9919
CN to ME and NA (M)	0.7711	0.1531	0.7123	0.8037	0.5232	0.7240
CN to ME and NA (X)	0.9724	0.4694	0.9918	0.9611	0.5763	0.9695
CN to UAE (M)	0.2414	0.5967	0.0345	0.9945	0.7371	0.9885
CN to UAE(X)	0.8928	0.4513	0.9300	0.8775	0.6717	0.8993

Given the presence of cointegration, the second step involved specifying and estimating the Error Correction Model. The ECM captures both short-term dynamics and the long-term equilibrium relationship. The error correction term (ECT) is incorporated into the short-term dynamics model. The general form of the ECM is

$$\Delta Y_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i \Delta X_{i,t} + \delta \mathrm{ECT}_{t-1} + v_t, \tag{4}$$

where Δ denotes first differences; γ_{i} are short-term coefficients; δ is the speed of adjustment coefficient; ECT$t-1$ is the lagged error correction term; and ν_{t} is the white noise error term. The ECM parameters are estimated using OLS. Diagnostic tests, including tests for autocorrelation (Breusch–Godfrey test) and heteroskedasticity (Breusch–Pagan test) are carried out to validate the model. Model Specification is therefore given by

Table 3 Results of ADF and PP tests for unit root in first differences

Variables	At 1st difference—ADF-Fisher Chi-square			At 1st difference—PP-Fisher Chi-square		
	Individual intercept	Individual intercept and trend	None	Individual intercept	Individual intercept and trend	None
TEU	0.0002	0.0061	0.0422	0.0002	0.0016	0.0005
TMC	0.0013	0.0017	0.0014	0.0013	0.0017	0.0014
TMG	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000
TUSA	0.0003	0.0022	0.0002	0.0003	0.0016	0.0003
SA to CN (M)	0.4661	0.9416	0.1632	0.0024	0.0161	0.0002
SA to CN (X)	0.0033	0.0155	0.0004	0.0033	0.0155	0.0004
SA to GE (M)	0.0025	0.0116	0.0001	0.0024	0.0110	0.0001
SA to GE (X)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SA to USA (M)	0.0006	0.0036	0.0001	0.0017	0.0186	0.0001
SA to USA(X)	0.0001	0.0005	0.0001	0.0001	0.0003	0.0001
CN to AF (M)	0.0098	0.0473	0.0006	0.0181	0.0844	0.0009
CN to AF (X)	0.0043	0.0165	0.0018	0.0046	0.0184	0.0019
CN to EU and CA (M)	0.0068	0.0153	0.0022	0.0104	0.0454	0.0022
CN to EU and CA (X)	0.0003	0.0015	0.0002	0.0003	0.0015	0.0002
CN to ME and NA (M)	0.0022	0.0146	0.0006	0.0200	0.1085	0.0011
CN to ME and NA (X)	0.0092	0.0388	0.0034	0.0102	0.0426	0.0036
CN to UAE (M)	0.0013	0.0045	0.0002	0.0015	0.0012	0.0002
CN to UAE(X)	0.0057	0.0296	0.0008	0.0074	0.0386	0.0010

$$\begin{aligned} \Delta TEU_t = \phi_1 + \sum_{l=1}^{p} \alpha_l \, \Delta TEU_{t-l} + \sum_{i=1}^{n} \sum_{l=1}^{p} \beta_{i,l} \, \Delta X_{t-l} + \\ + \delta_1 ECT_{t-1} + \zeta_t \end{aligned} . \tag{5}$$

With two dummy variables:

$$\begin{aligned} \Delta TEU_t = \phi_1 + \sum_{l=1}^{p} \alpha_l \Delta TEU_{t-l} + \sum_{l=1}^{n} \sum_{l=1}^{p} \beta_{i,l} \Delta X_{t-l} \\ + \delta_1 ECT_{t-1} + \gamma FC + \Omega C19 + \zeta_t \end{aligned} . \tag{6}$$

Φ, α, β, δ, γ, Ω are parameters and ζ is error term. X is represented by the respective variable (Table 7), which has a granger caused with TEU.

Table 4 The model data set

Variable	Description	Rationale
TEU	Colombo container throughput (TEU '000)	Dependent variable (Clarksons)
TMC	Total merchandise exports of China	Values (in million US dollars), capturing production flows outward to each production center (WTO)
TMG	Total merchandise export of Germany	
TUSA	Total merchandise export of the USA	
SA from CN (M)	South Asia imports from China	Values (in million US dollars), to capture the trade flows between Production Centers and South Asia. (WITS)
SA to CN (X)	South Asia exports to China	
SA from GE (M)	South Asia imports from Germany	
SA to GE (X)	South Asia exports to Germany	
SA From USA (M)	South Asia imports from USA	
SA to USA(X)	South Asia exports to USA	
CN From AF (M)	China imports from Africa	PoC benefits from cargo coming from and going to Europe, East and South Asia, the Persian Gulf, and East Africa. Container flows are effectively connected through the Colombo Port (SLPA 2023)
CN to AF (X)	China export to Africa	
CN from EU and CA (M)	China imports from Europe	
CN to EU and CA (X)	China exports to Europe	
CN from ME and NA (M)	China imports from Middle East and Central Asia	
CN to ME and NA (X)	China exports to Middle East and Central Asia	
CN From UAE (M)	China imports from UAE	
CN to UAE(X)	China exports to UAE	

3.4 Stage 4: Collection of data

The model was estimated using annual container throughput data (1991–2023) of the Port of Colombo obtained from the Clarksons research network (Clarksons 2023) and the total merchandise exports of China, Germany, USA, and India and the trade flows between production centers and South Asia were obtained from the data published by the World Trade Organization and its World Integrated Trade Solution (WITS) database (WITS 2023; WTO 2023). The model included two dummy variables to capture the uncertainty of trade flows. The dummies represented the financial crisis in 2008/2009 (IMF 2023) and COVID-19 in 2019 (Xu et al. 2021). Table 4 presents the data used.

3.5 Stage 5: model testing

The model was tested using in five scenarios using the container throughput of the Port of Colombo as the dependent variable: D(TEU). They are as follows:

Scenario 1: VECM model with China production center merchandise trade flows;
Scenario 2: VECM model with Germany production center merchandise trade flows;
Scenario 3: VECM model with USA production center merchandise trade flows;
Scenario 4: VECM model with China, Germany, and USA trade as production centers to South Asia; and
Scenario 5: VECM model with China production center trade to main regions associated with the PoC.

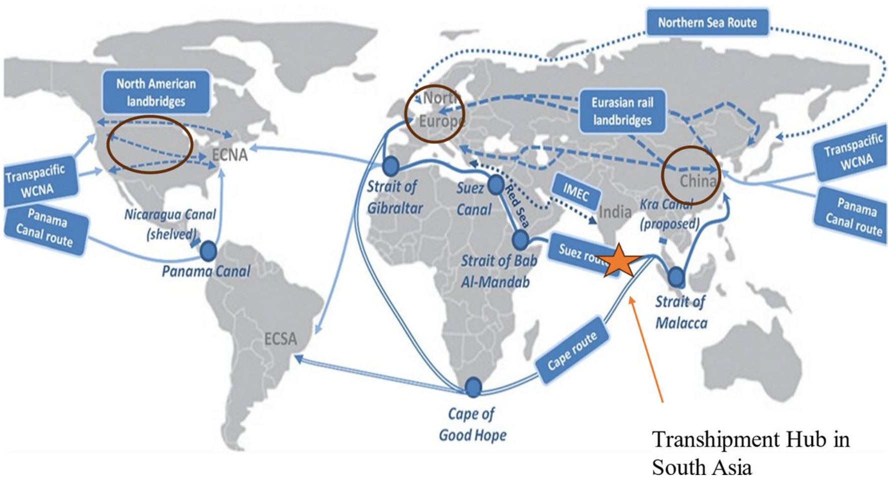

Fig. 2 Strategic Location of the Port of Colombo. Source: Based on Notteboom et al. (2024)

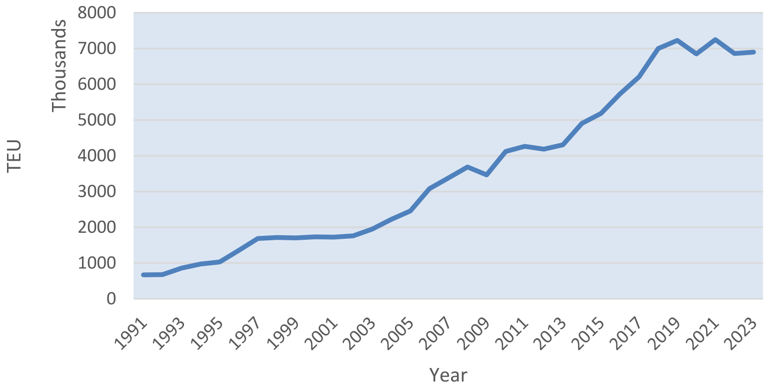

Fig. 3 Container Traffic at the Port of Colombo. Source: Authors, based on data from Clerkson shipping Intelligence (Clarksons 2023)

4 Analysis of results

4.1 Descriptive statistics

The Port of Colombo, as a transshipment port, benefits from cargo coming from and going to Europe, East and South Asia, the Persian Gulf, and East Africa. Much of this traffic transits (transships at) the port (SLPA 2023), due to its strategic location along the east–west main trunk routes (Kavirathna et al. 2021).

Figure 2 illustrates the strategic position of the Port of Colombo along key shipping routes linking major production centers. In addition to catering to its own region, the port serves as a crucial link between the Persian Gulf and East Africa, facilitating seamless maritime connectivity. Notteboom et al. (2024), citing the recent Red Sea crisis, highlight the significance of the Port of Colombo as a transshipment hub located in close proximity to the crisis area. During the crisis, the port had to handle a surge in traffic and redirect some small capacity vessels to the Hambantota International Port, situated in the southern part of Sri Lanka along the Belt and Road Initiative (BRI). This maneuver not only managed traffic levels but also ensured optimal service for cargo vessels. Such actions underscore the pivotal role of the Port of Colombo in the broader regional maritime landscape. As mentioned by Haralambides and Merk (2020), the main feature of a hub port is its location near the main shipping routes, as well as connections to large population and production centers. Therefore, the PoC is a best-case study for examining connections to production centers.

Figure 3 demonstrates the container throughput of the PoC from 1991 to 2023. Throughput has increased over the years, with a slight leveling off in 2019 due to COVID-19 and its impact on trade. Table 5 presents the descriptive statistics of the dependent and the seventeen independent variables chosen to specify our forecasting model.

The average annual container throughput at PoC in the period 1991 to 2023 stood at 3.517 million TEU, with a range from a minimum of 0.683 million to a maximum

Table 5 Descriptive statistics of dependent and independent variables

Variable	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	Jarque–Bera	Probability
TEU	3517900	3,380000	7249358	858392	2062323	0.4906	1.9791	2.4230	0.2978
TMC	1247414	1201612	3358163	91744	1001688	0.3112	1.7235	2.4370	0.2957
TMG	1037027	1120041	1636742	380096	428046	-0.2172	1.3932	3.3476	0.1875
TUSA	1100341	1056043	1754300	464773	421145	0.0528	1.4422	2.9457	0.2293
SA from CN (M)	36573	21928	108335	513	36952	0.4550	1.6323	3.2608	0.1958
SA to CN (X)	8703	9138	21133	178	7745	0.2343	1.4867	3.0328	0.2195
SA from GE (M)	8687	9046	18415	2015	5919	0.1261	1.3769	3.2603	0.1959
SA to GE (X)	6756	6641	13910	1952	4138	0.2019	1.5927	2.5904	0.2738
SA From USA (M)	18015	15962	47195	3231	13842	0.4056	1.8731	2.3295	0.3120
SA to USA(X)	30609	29886	65024	5705	20274	0.2604	1.5407	2.9009	0.2345
CN from AF (M)	38641	26307	110177	342	38500	0.5281	1.7997	3.0889	0.2134
CN to AF (X)	32054	18876	82447	828	31366	0.4366	1.5144	3.5882	0.1663
CN from EU and CA (M)	170816	119625	401554	15553	143645	0.4003	1.5241	3.4067	0.1821
CN to EU and CA (X)	244840	230402	577054	10892	202736	0.1477	1.3738	3.3009	0.1920
CN from ME and NA (M)	63726	43647	165746	1113	62533	0.4931	1.6730	3.3031	0.1918
CN to ME and NA (X)	58826	37743	146083	2160	55087	0.3595	1.4487	3.5326	0.1710
CN from UAE (M)	5308	2595	17055	37	6060	0.7627	1.9866	4.0523	0.1318
CN to UAE(X)	15479	11405	39035	543	13866	0.2728	1.4399	3.3006	0.1920

TEU twenty foot equivalent unit, *TMC* total merchandise exports of China, *TMG* Total Merchandise Exports of Germany, *TUSA* total merchandise exports of the USA, *SA* South Asia, *CN* China, *GE* Germany, *USA* United State of America, *AF* Africa, *EU* European Union, *CA* Central Asia, *ME* Middle East, *NA* North America, *UAE* United Arab Emirates, *M* import Flow, *X* export Flow of 7.249 million. Analyzing production center merchandise export statistics reveals China as the world's biggest exporter, followed by the USA and Germany. Regarding trade with South Asia, data show that the USA imports more than China from this region (Table 5). In South Asia, China records the highest import flows, while her maximum export flow heads towards the USA. Beyond South Asia, China's imports originate predominantly from Europe and Central Asia followed by trade with the Middle East and North America.

4.2 Statistical tests and econometric results

Following tests on stationarity, before modeling for identifying the long-run relationships among the trade flows, we tested for normality of data series and multicollinearity among exogenous variables. Jarque–Bera statistics indicated no significant deviations from normal distribution across all series, further supported by skewness and kurtosis values ranging between $+3$ and -3 (Table 5). We identified the existence of multicollinearity among variables, first through the correlation coefficients and then through the Granger Causality test. The correlation test results (Table 6) showed that there is a strong significant ($P=0.00$) linear association between all independent variables and the dependent variable (TEU), and there is a strong significant correlation ($r>0.8$, $P=0.00$) among the independent variables and TEU of the PoC.

To identify causality of variables with TEU, the Granger causality test was used and the results are shown in Table 7.

Based on the results of the Granger Causality test, out of the 17 variables examined, 10 variables exhibited significant Granger causality towards TEU, notably China (TMC), Germany (TMG), and the USA (TUSA). Exports from China, Germany, and the USA to South Asia also exhibited significant Granger causality towards TEU. Further analysis revealed that trade flows from China, including exports to Africa, the Middle East, North America, and the UAE, as well as China's imports from Europe and Central Asia, displayed significant Granger causality towards TEU at the Port of Colombo. These findings underscore the intricate relationship between international trade dynamics and container throughput at the Port of Colombo, highlighting the influence of major production centers and key trade routes on port activity.

After filtering variables according to the Granger Causality test, further analysis was carried out to identify short- and long-run relationships.

Figure 4 demonstrates a linear association between TEUs and the considered variables, while the total merchandise exports of China have a greater association than the other variables.

Based on Fig. 5, exports from South Asia to the USA exhibit a stronger linear association with the throughput of Colombo, compared to exports from Germany and China.

Further, China's imports from Europe and Central Asia exhibit a strong linear association with TEU of PoC (Fig. 6). Following diagnostic test results, scenarios-based modeling of trade flows was carried out.

Table 6 Pearson correlation coefficients and corresponding P-Values

Probability	TEU	TMC	TMG	TUSA	SA to CN (M)	SA to CN (X)	SA to GE (M)	SA to GE (X)	SA to USA (M)	SA to USA(X)	CN to AF (M)	CN to AF (X)	CN to EU and CA(M)	CN to EU and CA (X)	CN to ME and NA (M)	CN to ME and NA (X)	CN to UAE (M)	CN to UAE(X)
Person Correlation Coefficients	1	0.9667	0.9041	0.9398	0.9610	0.8865	0.8577	0.8396	0.9417	0.9629	0.8471	0.9526	0.9566	0.9523	0.8797	0.9494	0.9317	0.9202
significance ($P < 0.05$)		all are significant at 95% confidence level																

Table 7 Pairwise Granger causality test results (only causality towards TEU)

Pairwise Granger causality tests			
Lags: 2			
Null Hypothesis: the variable does not Granger cause TEU			
	No of observations	F-statistic	Prob
TMC	30	4.40417	0.0230
TMG	30	2.7727	0.0817
TUSA	30	6.0839	0.0070
SA to CN (X)	29	3.9034	0.0341
SA to GE (X)	29	3.3510	0.0521
SA to USA(X)	29	6.6123	0.0052
CN to AF (X)	27	3.7244	0.0404
CN from EU and CA(M)	27	4.5348	0.0224
CN to ME and NA (X)	27	3.4998	0.0479
CN to UAE(X)	27	4.3101	0.0263

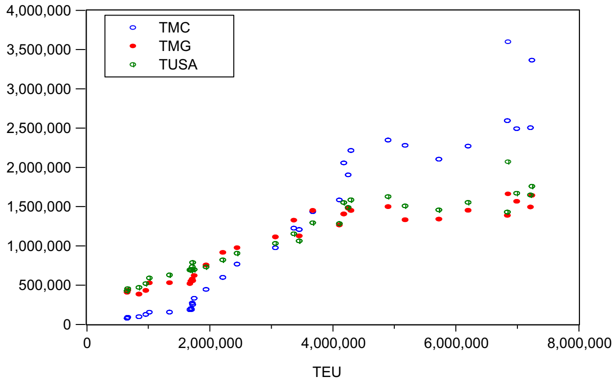

Fig. 4 Scatter Plot of TEUs associated with TMC, TMG, and TUSA

4.2.1 Scenario 1: VECM model with China as a production center merchandise trade flow

The modeling results of China's merchandise exports to the rest of world demonstrated a highly significant long-run relationship (the coefficient of ECT is negative and statistically significant; $P = 0.0064$) with the throughput of PoC (Table 8). Furthermore, past variations in TEUs have a persistent influence on current changes in throughput (0.5781 with $P = 0.0053$) with a positive relationship between the

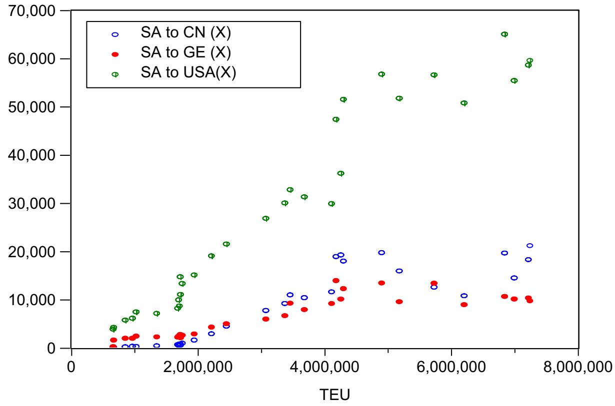

Fig. 5 Scatter Plot of TEUs with Trade towards SA from CN, GE, and USA

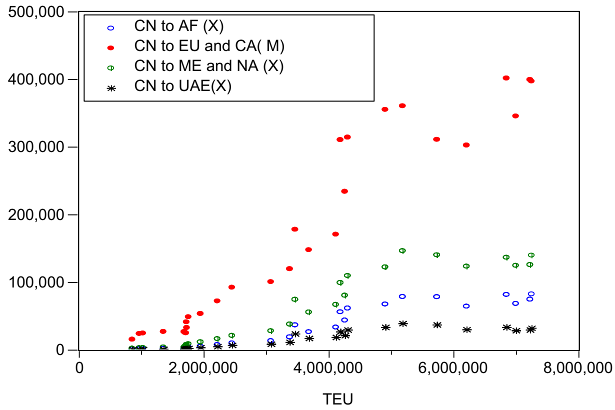

Fig. 6 Scatter Plot TEU with Trade direction of China

Table 8 Modeling results with China's production flow without uncertainty factors

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.578165	0.188472	3.067640	0.0053
D(TMC)	1.046403	0.255593	4.094025	0.0004
D[TMC(-1)]	− 1.126999	0.363930	− 3.096744	0.0049
ECT (-1)	− 0.255247	0.085471	− 2.986343	0.0064
C	91571.34	62804.30	1.458043	0.1578

Breusch–Godfrey Serial Correlation LM Test F-Statistic (1.839), Prob. F (2, 22) 0.1825

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (0.9751), Prob. F (4, 24) 0.4395

Table 9 Modeling results with China's production flow and uncertainty factors

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.584339	0.194480	3.004621	0.0065
D(TMC)	0.991980	0.272100	3.645646	0.0014
D[TMC(-1)]	− 1.084265	0.385760	− 2.810727	0.0102
ECT(-1)	− 0.184290	0.115999	− 1.588723	0.1264
COVID-19	− 190505.7	206174.9	− 0.924001	0.3655
FC	43436.49	137311.0	0.316337	0.7547
C	97506.46	66220.05	1.472461	0.1551

Breusch–Godfrey Serial Correlation LM Test F-Statistic (2.8996), Prob. F (2, 20) 0.0784

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (1.0179), Prob. F (6, 22) 0.4395

variation in TMC and in TEUs, implying that an increase in China's merchandise exports leads to an increase in PoC throughput (1.0464), and a decrease in China's merchandise exports in the previous period leads to an increase in throughput in the current period (− 1.1269). The negative coefficient of Error Correction Term (0.255247) suggests that if the system deviates from its long-run equilibrium by one unit in the previous period, it will be corrected by approximately 0.255247 units in the current period. When the above model is modified to incorporate uncertainties stemming from the COVID-19 pandemic and the financial crisis as external shocks, neither of these variables influences significantly the modeling results of PoC throughput (Table 9).

The model retains its validity criteria, as evidenced by the coefficient values of the uncertainty variables COVID (P: $0.3655 > 0.05$) and FC (P: $0.7547 > 0.05$). The modeling results show a persistent influence of past variations on the current changes in TEUs, indicating a strong feedback mechanism within the global trade network. The positive relationship between changes in China's merchandise exports and TEUs underscores the symbiotic nature of trade dynamics, whereby an increase in China's exports tends to stimulate demand for shipping services, reflected in the rise in TEUs handled at the port. Our findings suggest that while external shocks

Table 10 Modeling results with Germany's production flows without uncertainty factors

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.314530	0.188108	1.672074	0.1075
D(TMG)	1.292031	0.376412	3.432492	0.0022
D[TMG(-1)]	− 0.789281	0.449048	− 1.757678	0.0916
ECT (-1)	− 0.078982	0.067549	− 1.169256	0.2538
C	129,889.5	58,719.27	2.212043	0.0367

Breusch–Godfrey Serial Correlation LM Test F-Statistic (0.1956), Prob. F (2, 22) 0.8237

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (0.8056), Prob. F (4, 24) 0.5337

Table 11 Modeling results of Germany's product flows (short-run model)

Variable	Coefficient	Std. Error	t-statistic	Prob
TEU(-1)	1.030187	0.185284	5.560048	0.0000
TEU(-2)	− 0.061276	0.176953	− 0.346285	0.7321
TMG	1.244729	0.372775	3.339088	0.0027
TMG(-1)	− 0.953758	0.410298	− 2.324546	0.0289
C	− 25504.36	126507.4	− 0.201604	0.8419

Breusch–Godfrey Serial Correlation LM Test F-Statistic (1.8432), Prob. F (2, 22) 0.1819

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (1.8263), Prob. F (4, 24) 0.1567

may temporarily disrupt trade flows, the underlying relationship between China's merchandise exports and global trade remains robust. The ability of the model to accommodate uncertainty variables underscores its adaptability in capturing the evolving dynamics of international trade and their influence on the hub port.

4.2.2 Scenario 2: VECM model with Germany's merchandise trade flow

The modeling results of Germany's exports to the rest of the world demonstrated an insignificant long-run relationship (the coefficient of ECT is negative and but statistically insignificant; $P=0.25$) port throughput (Table 10). Therefore, modeling was carried out to identify any short-run relationships (Table 11).

The TEU coefficient suggests that, *ceteris paribus*, a one-unit increase in the lagged value of TEU leads to a 1.03018 unit increase in the current period's TEUs. This indicates a positive autocorrelation effect, meaning that the past year values of TEU have a persistent influence on the current volumes of TEU. However, longer period demonstrates insignificant relationship. The coefficient of TMG indicates that a one-unit increase in the current period's total merchandise exports of Germany results in a 1.2447 unit increase in TEUs, *ceteris paribus*. This suggests a positive relationship between variations in Germany's merchandise exports and PoC throughput, implying that an increase in Germany's exports tends to lead to an increase in TEUs. Instead, a one-unit increase in the lagged value of TMG leads to a − 0.9537 unit decrease in the current period's TEU, holding other variables constant. This indicates an inverse relationship between variations in Germany's merchandise exports from the previous period and current PoC throughput. This suggests that a decrease in Germany's exports in the previous period tends to lead to an increase in PoC TEUs in the current period. Holding the model validly criteria the same, the inclusion of COVID-19 and the 2008–9 financial crisis in the model showed insignificant results. The modeling results only demonstrated short-run relationship between changes in Germany's merchandise exports (TMG) and the PoC TEUs, highlighting both direct and inverse relationships. A one-unit increase in current TMG results in a substantial increase in TEUs, reflecting the interconnectedness between Germany's export activities and global trade flows. Conversely, a decrease in Germany's exports of the previous period correlates with an increase in TEUs

Table 12 Modeling results with USA's trade flows without uncertainty

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.599080	0.166952	3.588337	0.0015
D(TUSA)	1.533302	0.309158	4.959609	0.0000
D[TUSA(-1)]	− 1.771995	0.474173	− 3.737020	0.0010
ECT(-1)	− 0.157162	0.059160	− 2.656573	0.0138
C	85965.82	48201.81	1.783456	0.0872

Breusch–Godfrey Serial Correlation LM Test F-Statistic (0.2189), Prob. F (2, 22) 0.8051

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (1.2345), Prob. F (4, 24) 0.3228

in the current period. This suggests a compensatory effect whereby fluctuations in German exports cause shifts in shipping demand. Within the scope of the analyzed data, these external shocks do not exert any discernible impact on the relationship between TEUs and Germany's merchandise exports.

4.2.3 Scenario 3: VECM model with USA's merchandise trade flows

The coefficient of 0.559990 underscores a compelling observation whereby a mere one-unit rise in the previous period's D(TEU) leads to a 0.59990 unit increase in the current period's D(TEU). This suggests a lingering impact of historical shifts on present TEU dynamics (Table 12). Additionally, the coefficient of 1.5333 highlights an intriguing correlation whereby each unit increase in USA's total merchandise exports triggers a robust 1.5333 units surge in D(TEU), signifying a positive association between TUSA and TEUs. Conversely, the coefficient of − 1.7719 unveils a noteworthy contrast whereby a one-unit escalation in the lagged TUSA results in a significant − 1.7719 unit decline in the current D(TEUs), indicating an inverse relationship between TUSA and TEUs. Moreover, the Error Correction Term (ECT) coefficient of − 0.15716 sheds light on the model's adaptive prowess that a one-unit

Table 13 Modeling results with USA's trade flows with uncertainty

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.590139	0.179898	3.280403	0.0034
D(TUSA)	1.488183	0.389433	3.821409	0.0009
D[TUSA(-1)]	− 1.707193	0.504095	− 3.386651	0.0027
ECT(-1)	− 0.125974	0.083607	− 1.506728	0.1461
COVID-19	− 66614.43	197041.7	-0.338073	0.7385
FC	56804.15	121122.9	0.468979	0.6437
C	85465.51	54163.98	1.577903	0.1289

Breusch–Godfrey Serial Correlation LM Test F-Statistic (0.1839), Prob. F (2, 20) 0.8334

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (0.9428), Prob. F (6, 22) 0.4850

deviation from equilibrium in the prior period is rectified by approximately 0.15716 units in the current period, showcasing the VECM's resilience in maintaining equilibrium.

Despite the model's robustness, incorporating critical variables such as those pertaining to COVID-19 and 2008–9 financial crisis (Table 13) lacks statistical significance (coefficient 66,614 for COVID-19; $P=0.7385$ and 56,804 for FC; $P=0.6437$). This suggests the absence of control effects from external shocks on the relationship between TUSA and TEUs, underscoring the model's independence from extraneous influences.

The coefficients pertaining to the USA's Total Merchandise Export (TUSA) unveil intriguing correlations. A unit increase in TUSA triggers a robust surge in D(TEU), emphasizing the positive association between US export activities and global shipping demand. However, the model also reveals a noteworthy contrast, with a one-unit escalation in lagged TUSA resulting in a significant decline in the current D(TEU), indicating an inverse relationship between TUSA and TEU. This suggests a complex interplay of factors influencing US export and import dynamics and their impact on global trade flows. This showcases the model's robustness in accurately depicting the long-term relationship between TUSA and PoC throughput. The model is independent from extraneous influences and capable of discerning the underlying drivers of global trade dynamics.

4.2.4 Scenario 4: VECM model with China, Germany, and USA trade flows to South Asia

The coefficient of 0.273355 for D[TEU(-1)] is not statistically significant, suggesting that the lagged value of D(TEU) does not exert a significant influence on the current period's D(TEU) (Table 13). Conversely, D(South Asia to China (Export)) exhibits a highly significant coefficient of 58.78331, indicating a strong positive relationship between changes in South Asia's exports to China and changes in TEUs. However, D(South Asia to Germany (Export)) and D(South Asia to USA (Export)) both have coefficients of 40.94570 and − 28.66709, respectively, which are not statistically significant, suggesting that changes in South Asia's exports to Germany

Table 14 Modeling results with China, Germany, and USA trade flows to South Asia without uncertainty

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.273355	0.188935	1.446818	0.1614
D(SA to CN (X)	58.78331	26.38320	2.228059	0.0359
D(SA to GE (X)	40.94570	43.82660	0.934266	0.3599
D(SA to USA(X)	−28.66709	20.53375	−1.396096	0.1760
ECT(-1)	−0.353164	0.124024	−2.847545	0.0091
C	170655.8	64283.89	2.654721	0.0142

Breusch–Godfrey Serial Correlation LM Test F-Statistic (0.03399), Prob. F (2, 21) 0.9666

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (0.5461), Prob. F (5, 23) 0.7395

Table 15 Modeling results with China, Germany, and USA trade flows to South Asia with uncertainty

Variable	Coefficient	Std. error	t-statistic	Prob
D[TEU(-1)]	0.409528	0.198380	2.064361	0.0516
D(SA_CN_X)	60.92626	25.61593	2.378452	0.0270
D(SA_GE_X)	37.37200	43.33593	0.862379	0.3982
D(SA_USA_X)	− 26.89571	20.32775	− 1.323103	0.2000
ECT(-1)	− 0.400463	0.137761	− 2.906931	0.0084
COVID-19	− 210332.1	192971.8	− 1.089963	0.2881
FC	− 218785.1	143525.9	− 1.524360	0.1423
C	182605.4	62561.14	2.918831	0.0082

Breusch–Godfrey Serial Correlation LM Test F-Statistic (1.5391), Prob. F (2, 19) 0.2401

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (0.5871), Prob. F (7, 21) 0.7589

and to the USA do not significantly impact TEUs. The Error Correction Term (ECT) coefficient of − 0.3531 is statistically significant, indicating the presence of a correction mechanism towards equilibrium. This implies that deviations from the long-run equilibrium in the previous period are corrected by approximately 0.3531 units in the current period. Overall, while South Asia's exports to China play a significant role in influencing the volume of TEUs, exports to Germany and the USA do not demonstrate statistically significant effects, and the model exhibits a corrective mechanism to maintain equilibrium over time (Table 14).

Despite the model's robustness, incorporating critical variables such as those pertaining to COVID-19 and the financial crisis (Table 15) lacks statistical significance their coefficients (−210,332 for COVID-19, $P=0.2881$; −2187for FC, $P=0.1423$). This suggests the absence of control effects from external shocks on the relationship between South Asian exports to China, Germany, and USA and the volume of TEUs, underscoring the model's independence from extraneous influences.

Table 16 Modeling results with China's Trade flows to main shipping region associated with the PoC without uncertainty

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.248114	0.157775	1.572581	0.1301
D(CN_AF_X)	21.07910	18.60279	1.133115	0.2694
D(CN_EU_CA_M)	9.914325	3.699118	2.680186	0.0137
D(CN_ME_NA_X)	− 12.96240	4.219934	− 3.071705	0.0056
D(CN_UAE_X)	− 64.52154	30.53834	− 2.112805	0.0462
ECT (-1)	− 0.338365	0.111284	− 3.040548	0.0060
C	111793.5	60273.91	1.854757	0.0771

Breusch–Godfrey Serial Correlation LM Test F-Statistic (1.4379), Prob. F (2, 20) 0.2609

Heteroskedasticity Test: Breusch–Pagan–Godfrey F-Statistic (0.3976), Prob. F (6, 22) 0.8725

The results highlight the significant role of South Asia's exports to China in influencing global shipping demand, while exports to Germany and the USA show less pronounced effects. The model's corrective mechanism ensures equilibrium in trade dynamics over time, enhancing its reliability in forecasting long-term trends. Additionally, the model's independence from external shocks underscores its robustness in capturing the underlying drivers of global trade dynamics, providing valuable insights for policymakers and stakeholders in navigating the complexities of the global economic landscape.

4.2.5 Scenario 5: VECM model with China's trade flows to main shipping region associated with the PoC

The coefficient of 0.24811 for D(TEU(-1)) is not statistically significant, indicating that the lagged value of D(TEU) does not exert a significant influence on the current period's D(TEU) (Table 16). Conversely, significant coefficients are observed for various trade flows: D(China to Africa (Export)) exhibits a highly significant coefficient of 58.78331, suggesting a substantial impact of China's exports to Africa on the volume of TEUs. Similarly, D(China from Europe and Central Asia (Import)) and D(China to Middle East and North America (Export)) both display significant coefficients of 9.9143 and – 12.9624, respectively, indicating notable effects of trade flows from these regions on TEU. Moreover, D(China to UAE (Export)) shows a significant coefficient of – 64.5215, implying a considerable influence of China's exports to the UAE on TEU. The Error Correction Term (ECT) coefficient of – 0.3383 is also statistically significant, suggesting the presence of a correction mechanism towards equilibrium. This implies that deviations from the long-run equilibrium in the previous period are corrected by approximately 0.3383 units in the current period. Additionally, after incorporating dummy variables for COVID-19 and the financial crisis, the model's validity remains intact. Notably, the dummy variable for the financial crisis (FC) is significant in the long-run model, highlighting its substantial impact on the relationship between the trade variables (Table 17).

Table 17 Modeling results with China's trade flows to main shipping region associated with the PoC with uncertainty

Variable	Coefficient	Std. Error	t-statistic	Prob
D[TEU(-1)]	0.171564	0.157652	1.088241	0.2894
D(CN_AF_X)	33.50574	18.24616	1.836317	0.0812
D(CN_EU_CA_M)	7.077250	3.753682	1.885415	0.0740
D(CN_ME_NA_X)	– 8.534194	4.441889	– 1.921298	0.0691
D(CN_UAE_X)	– 109.2734	34.51407	– 3.166054	0.0049
ECT (-1)	– 0.295134	0.116603	– 2.531098	0.0199
COVID-19	– 100017.1	168234.0	– 0.594512	0.5588
FC	296851.7	141207.6	2.102235	0.0484
C	127285.8	57329.07	2.220267	0.0381

China's exports to Africa, Europe and Central Asia, the Middle East, North America, and the UAE demonstrate notable effects on TEU levels, highlighting the importance of these trade relationships in shaping global shipping demand. These findings underscore the interconnectedness of trade flows and seaborne transport, where shifts in trade patterns have tangible implications for shipping activities. The financial crisis also significantly impacted the variation of TEUs at the Port of Colombo (PoC) in this model. The significant Granger causality relationship with TEUs shows the importance of global trade patterns in shaping port activity. Additionally, the findings highlight the significance of exports from these production centers to South Asia, indicating the region's role as a vital market for goods transported through the PoC. Delving deeper into specific trade flows, our results show that exports from China to Africa, the Middle East, North America, and the UAE, alongside China's imports from Europe and Central Asia, exert a significant influence on TEUs at the PoC. This emphasizes the interconnectedness of trade routes and the port's function as a transshipment hub facilitating trade across multiple regions. The financial crisis notably influenced this category, as the model deals with trade flows involving some countries affected by the financial crisis of 2008/2009.

5 Discussion and policy implications

The efficient movement of goods from production centers to demand points relies heavily on maritime transportation. Transshipment ports play a crucial role in maritime supply chains (MSC), being crucial nodes that connect these links, particularly in relay networks which interconnect regions in container trade flows. A port's capacity is essential for maintaining a competitive edge and expanding market share. Investing in new port capacity should be justified by increasing demand for port services; yet, demand forecasting in such a competitive environment is challenging due to its unpredictability and fluctuations. Port capacity planning requires sophisticated analytical approaches to match cargo flow projections and future demand estimations with the development and acquisition of suitable infrastructure (Parola et al. 2021). Forecasting models are subject to epistemic uncertainty due to model and parameter uncertainties (Eskafi et al. 2021). External shocks, such as the COVID-19 outbreak, exemplify volatile conditions, creating uncertainty in cargo flows and thus complicating decision-making for port development projects (Notteboom and Haralambides 2020). Therefore, forecasting models provide valuable insights into port services demand, and soft computing models have gained attention for capturing both linear and nonlinear relationships between input data and port throughput (Munim and Schramm 2021).

Our study finds that transshipment demand is influenced not only by trade flows from production centers but also by the global trade passing through the port. Any disruption at a transshipment port can impact significantly the entire MSC, highlighting the need for stable port operations. Deciding on transshipment capacity involves the use of forecasting techniques to align with fluctuating demand. The literature suggests that China, the USA, and Germany are dominant production centers globally (WTO 2023; UNCTAD 2022). The econometric model developed in this paper, using data from a case transshipment hub port and other influential variables, demonstrates that variability in throughput can be explained by merchandise exported globally by these production centers. International trade flows from these centers to South Asia, leveraging the strategic location of the Port of Colombo (PoC) as a transshipment hub, show a significant association with TEUs at PoC. Cointegration tests and VECM models reveal a long-term association between China's merchandise exports and PoC throughput, suggesting that PoC can expect higher TEU volumes with China's economic growth. Thus, expanding PoC's containerized cargo capacity helps enhance its competitive position in the region.

The PoC serves several submarkets as a transshipment hub. Given India's status as a major exporter in South Asia and its exclusion from the Belt and Road Initiative (BRI), PoC plays a critical role in connecting Indian subcontinent ports to global shipping networks. Upgrading PoC to a global hub is therefore highly advantageous for the region. The modeling results indicate that external shocks, such as economic crises and the COVID-19 pandemic, did not significantly influence PoC's international trade flows, except for the financial crisis of 2008–9.

According to the five-scenario analysis, the PoC's throughput demonstrates a long-term econometric relationship with China's global merchandise flows and South Asian exports to China. Furthermore, the volume of TEUs at the PoC has a long-run relationship with China's imports to Europe and Central Asia and exports to the Middle East, North America, and the UAE. These relationships remain strong despite the financial crisis and the COVID-19 pandemic. This analysis demonstrates the PoC's strength in building international trade links between port regions and China, a major production center. Upgrading the PoC by enhancing its capacity to handle increased volumes can further solidify its position as a key player in Indian Sub-continent and global trade, thereby supporting regional economic growth.

The paper contributes to the strategic planning of transshipment ports by providing a robust forecasting technique. Understanding future container throughputs is crucial for port authorities and stakeholders in making informed decisions related to infrastructure development, resource allocation, and capacity planning. By integrating international trade flows from global production centers, the paper acknowledges the interconnectedness of global trade networks (Dragan et al. 2021). This approach recognizes that container throughputs at transshipment ports are influenced by the dynamics of international trade, and a forecasting model that considers these factors provides a more accurate representation of future port activities. Furthermore, accurate forecasting enables transshipment ports to optimize their operational efficiency. With a better understanding of future container throughputs, ports can plan their operations more effectively, reduce congestion, optimize resource allocation, and enhance overall performance (Gosasang et al. 2018; Chen et al. 2023a, b).

Finally, the paper adds to the body of knowledge in port management, logistics, and international trade forecasting. The findings of this research have practical implications for the efficient and resilient management of transshipment ports amid dynamic global trade scenarios, particularly for a single transshipment hub serving an entire port region. These insights inform strategic investments, foster robust trade partnerships, and support the continuous adaptation necessary for maintaining a competitive edge in the global maritime network.

The paper presents several significant implications for transshipment hubs, particularly those strategically located along major maritime routes serving both regional and international markets. Our study suggests that port managers can estimate the demand for the services of a transshipment hub by analyzing trade flows from global production centers and the international maritime network, considering the port's pivotal role within relay and hub-and-spoke networks. The use of Granger causality is invaluable for identifying causal relationships between variables. This acts as a variable reduction method, isolating variables that are causally related to the dependent variable. The process facilitates the application of the Engle–Granger two-step procedure, which incorporates different lag terms as part of a machine learning approach to develop the optimal model. This methodology aims to reduce forecasting errors, maintain validity, and enhance the precision of demand forecasts. Ultimately, it informs strategic decisions on infrastructure development and capacity planning, ensuring that ports remain competitive and responsive to dynamic global trade conditions.

6 Conclusions

The demand for transshipment hub-port capacity is intricately linked to the trade dynamics of global production centers. Understanding and adapting to the changing dynamics of such centers is crucial for effective port management and for ensuring the resilience of maritime supply chains. The paper presents the results of an econometric forecasting model for a transshipment port, considering international trade flows from global production centers and explicitly addressing the uncertainties inherent in the world trade environment. China exerts a profound and enduring influence on the Port of Colombo, particularly in facilitating outbound trade flows, notably as a key transshipment hub within the Indian subcontinent. The port's trade dynamics are intertwined with Chinese production networks, serving as a crucial channel for goods destined for global markets. Notably, the port's reliance on Chinese manufacturing surpasses that of other major production centers, such as the USA and Germany. It is worth emphasizing that despite India's substantial size and its role as a feeder market for the Port of Colombo, its impact on the port's throughput growth remains relatively modest. Additionally, the relationship between production flows from the production center and the transshipment port traffic is more sensitive to financial crises.

The paper contributes to the existing body of knowledge in port demand modeling in several ways. First, the study re-emphasizes the critical role of transshipment ports as strategic nodes in global supply chains in the existing literature and brings about a novel perspective in research, focusing on transshipment ports and the impact of global trade dynamism, influenced by major production centers. Second, unlike previous studies, our research incorporates a comprehensive demand forecasting methodology that considers international trade dynamics between production centers and foreland nations, providing a more thorough perspective on demand prediction for transshipment hubs. Third, in its modeling design, we employ the Granger causality test to identify 17 trade directions that have a causal impact on the selected transshipment hub. This systematic approach to causality provides a robust foundation for predicting demand. Next, we develop a demand forecasting model of a transshipment hub, related to merchandise exports from global production centers, using the Engle–Granger causality test. This model incorporates trade flows between the hub's region, major production centers, and other countries along major shipping routes. Fifth, the model developed with two key economic disruptions explains the impact of exogenous shocks to port traffic, adding a layer of realism and adaptability to forecasting. Sixth, the model utilizes advanced time series analysis techniques to capture the uncertainties and dynamics of trade flows while incorporating multiple variables, including merchandise exports, regional trade, and trade flows along major shipping routes, ensuring a multifaceted analysis that aligns with real-world complexities. Lastly, the empirical validation and practical relevance of the model offer practical insights for port authorities and stakeholders to make informed decisions regarding port planning, development, and operations based on robust demand forecasts.

Our work can be extended by exploring additional variables that can mediate trade flows, such as trading agreements, transport costs, and shipping industry dynamics, including port choice selection parameters, to improve the accuracy of predictions in the context of transshipment ports and global trade flows. Furthermore, research focused on transforming a transshipment port into a global hub, particularly in strategic locations that play a crucial role in maritime supply chains, by connecting with the world's major production centers, is essential for further study. This would enhance understanding of the port's strategic importance and its potential to bolster global trade connectivity.

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