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The Relationship Between Shipping Demand and Macroeconomic Determinants in Türkiye: An ARDL Approach

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Abstract This study aims to identify the short- and long-run macroeconomic determinants of shipping demand in Türkiye and examine whether structural breaks alter these relationships. Monthly data spanning January 2012 to June 2025 are analyzed using an autoregressive distributed lag model and an error correction model. In addition, Augmented Dickey-Fuller, Zivot-Andrews, and Bai-Perron tests were incorporated to identify any structural breaks and assess stationarity. Based on the analysis of empirical results, the Industrial Production Index was determined to be the most significant long-run variable in predicting long-term shipping demand. Conversely, there is a significant negative impact of crude oil prices on shipping activity. The Baltic Dry Index and Global Economic Policy Uncertainty were both determined to be insignificant in predicting long-term shipping demand. However, they each had an immediate negative impact on shipping demand in the short run, exhibiting lagged response effects. The model showed that stable long-run equilibrium exists, which indicates that the model accommodates relatively rapid adjustments. There was evidence of a regime shift occurring in March 2019, which indicates a structural break in the market. This study provides empirical evidence related to maritime policy development through macroeconomic shifts to enhance the understanding of how fluctuations in the macroeconomy affect.

Keywords Shipping demand · maritime resilience · economic policy uncertainty · industrial production index · transport policy

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Acronyms			
ADF	Augmented dickey-fuller	GEPU	Global economic policy uncertainty
AIC	Akaike information criterion	INPI	Industrial production index
ARDL	Autoregressive distributed lag	LN	Natural logarithm
BDI	Baltic dry index	OIL	Crude oil
COM	Commodity price	SD	Shipping demand
COVID-19	Coronavirus disease	SVAR	Structural panel vector autoregressions
CUSUM	Cumulative sum	URT	Unit root test
ECM	Error correction model	VAR	Vector autoregression

Introduction

Shipping plays a critical role in the expansion and development of global trade owing to its advantages in carrying capacity and cost-effectiveness (Alizadeh & Talley, 2011; Jugović et al., 2015). While these features make shipping an essential component of global trade, the sector also exhibits its own vulnerabilities. Large-scale global shocks and geopolitical events have profoundly impacted the global maritime industry (Khan et al., 2021; Notteboom et al., 2021; Suárez-de Vivero & Mateos, 2017). Additionally, financial and economic crises, price fluctuations in global markets, uncertainties in economic policies, trade wars, geopolitical risks, and random shocks exert pressure on maritime markets, negatively affecting sectoral stability (Drobetz et al., 2021; Toygar & Yıldırım, 2024; Xu et al., 2024). In this unstable environment, maritime freight rates in shipping play a central role in shaping the balance of supply and demand, while also directly influencing the income and profitability levels of stakeholders in the sector (Ke et al., 2024). Consequently, maritime freight rates across different shipping categories exhibit distinct volatility patterns driven by segment-specific macroeconomic and demand-side fundamentals, revealing the unique market dynamics of each category (Drobetz et al., 2012; Tsouknidis, 2016). Therefore, effective management and planning of demand are crucial for preserving the quality of shipping services and ensuring environmental sustainability (Aytekin et al., 2024). Understanding the process of determining freight rates in shipping and the dynamics that shape this process is vital for strategic decision-making by practitioners, economists, and regulatory bodies within the sector (Ke et al., 2024). However, demand dynamics, particularly in countries with geostrategic locations, are influenced by sector-specific fluctuations in shipping.

A regional study that has the potential to affect global outcomes is key to understanding how structural and policy changes in the shipping industry over the past few years may have impacted shipping demand and Türkiye's geopolitical and economic situation. The country has a substantial role in the global logistics system due to its geostrategic location as a central point on the trade routes and its developing seaport infrastructure (Toygar & Yıldırım, 2024). Türkiye's distinctive geographical features, its three sides surrounded by water and numerous hub seaports that provide transit service and connection to the two other continents, demonstrate its importance to the overall shipping industry. Shipping is the most essential aspect of these foreign trade activities. In recent years (between 2021 and 2023), over 90% of imports and 78-80% of exports were conducted by sea, based on volume (Ministry of Trade of the Republic of Türkiye, 2024). Figure 1 was created using cargo handling volume data provided by the seaport authorities of Türkiye. From January to December 2024, a total of 531.7 million cargo units were handled in seaport operations across the administrative borders of 41 seaport authorities (MTI-GDMA, 2025).

Figure 1

Geographical distribution and density heatmap of seaports in Türkiye, categorized by cities



Although previous empirical studies have investigated the factors determining global shipping demand (Michail, 2020; Nomikos & Tsouknidis, 2023), analyses using long-term, high-frequency data for Türkiye remain limited. Existing national research focuses on adjacent logistics operations and regional strategies (Aytekin et al., 2024; Özen et al., 2020); however, the time-series evaluation of the interaction between aggregate shipping demand and macroeconomic uncertainties within the Turkish context has not been established. This study aims to identify the primary factors influencing shipping demand in Türkiye and address a gap in the existing literature by using econometric modeling techniques. The analysis focuses on the factors affecting shipping demand in the Turkish shipping sector using monthly data from 2012 to 2025. The research uses the autoregressive distributed lag (ARDL) model to identify both short-run and long-term relationships in the case of shipping demand as the dependent variable (SD) and industrial production index (INPI), Global Economic Policy Uncertainty (GEPU), Baltic Dry Index (BDI), commodity price (COM), and crude oil price (OIL) as independent variables. Against this background, three research questions guide the empirical analysis.

(1) Which of the selected macroeconomic variables (INPI, GEPU, BDI, COM, and OIL) maintain a statistically significant long-run cointegrating relationship with shipping demand in Türkiye over the 2012-2025 period?

(2) Do these variables produce statistically significant short-run effects on shipping demand, and if so, at what lag order and with what sign?

(3) Do the structural breaks identified in the sample period alter the estimated long-run equilibrium parameters?

The remaining sections of this paper have been structured into different sections. In Section 2, we discuss previous research into shipping demand determinants and the corresponding resilience of the maritime industry. Section 3 of the research shows how data collection took place, describes the variables used in the analysis, and details the methodology for estimating the ARDL model. The bounds testing results, along with both long-run coefficients and the error correction model, are presented in Section 4. Section 5 addresses our findings and discusses their possible effects on the maritime industry of Türkiye through various policy implications. Section 6 summarizes the conclusions of this study and provides any theoretical contributions it may make. Section 7 includes the limitations of this research and possible future directions for research within this area.

Theoretical Framework

Resilience, as a more comprehensive concept than vulnerability, refers to a multidimensional process that encompasses a system's response to a disruptive event, its preparedness before the event, and its recovery capacity after

the event (McIntosh & Becker, 2019). This process involves the system's exposure, sensitivity, and adaptive capacity and emphasizes its ability to reorganize and transform. The implementation of resilience varies depending on the unique dynamics and contextual requirements of each sector (Akpinar & Özer-Çaylan, 2023).

In the context of the shipping sector, resilience is defined as the capacity of a shipping organization or system component to withstand disruptions and return to the desired level of operational performance following such events (Gu & Liu, 2025). However, the shipping sector exhibits economic vulnerability due to increasingly integrated supply chains through globalization, excess capacity, volatile freight rates, and uncertain fuel prices (Koray et al., 2025; Lau et al., 2024; Wendler-Bosco & Nicholson, 2020). The sector has undergone significant tests of its resilience and adaptive capacity in response to various past economic and geopolitical shocks. In particular, the 2008-2009 global financial crisis and the COVID-19 pandemic have revealed systemic vulnerabilities by causing severe declines in port performance through sudden drops in demand and disruptions in supply chains. Moreover, events such as the blockage of the Suez Canal, major natural disasters, U.S.-China trade tensions, and the geopolitical implications of the Russia-Ukraine war have led to severe congestion in shipping systems, increased freight rates, and suspended shipments (Notteboom et al., 2021; Rožić et al., 2022). These shocks have made the concept of resilience in shipping a priority topic in academic research and sectoral policy, especially in the post-2019 period (Lau et al., 2024). While periodic disruptions following such shocks are considered normal, they can lead to increased operational costs and create significant imbalances in the business environment (Rožić et al., 2022). In this context, resilience is not solely about immediate responses to shocks but also about the extent to which systems are prepared for such shocks in advance. Therefore, it is imperative to enhance the resilience capacity of key sectoral components—particularly ports and maritime networks—both at the individual and systemic levels (Dhanak et al., 2021; Li et al., 2022). Given this vulnerability, it is essential to examine how different segments within shipping experience and respond to these disruptions differently.

Shipping is categorized into various segments that enable the movement of different types of cargo along specific routes. One such category, bulk cargo shipping, is further classified into two primary subcategories: liquid and dry cargo. While shipping is significantly affected by fluctuations in global markets, bulk cargo shipping is particularly vital within the shipping sector (Nomikos & Tsouknidis, 2023). The bulk cargo market demonstrates greater volatility than other shipping types, especially in relation to international economic stability, changes in trade volume, and national policies (Gu & Liu, 2022). Tanker shipping, a vital sub-sector of liquid cargo shipping, plays a crucial role in ensuring global energy supply security. This mode of transport facilitates the sustainability of global energy trade by delivering energy resources, such as oil and refined products, to various regions. However, due to the diversity of products transported and the complex structure of trade routes, academic studies on tanker shipping have been more limited compared to other shipping segments. In particular, supply-demand imbalances in refined petroleum products are becoming increasingly significant in global trade due to production surpluses in certain regions (Bai & Lam, 2021). Conversely, container shipping relies on two fundamental demand factors that influence the functioning of global trade: fixed demand due to long-term contracts and variable demand stemming from the spot market. While long-term contracts provide relatively stable income through negotiated freight rates between the parties, freight rates in the spot market are determined dynamically based on competitive conditions and demand fluctuations (Wang & Meng, 2021). Freight rates in the container shipping market can experience significant short-term fluctuations, which are also affected by macroeconomic variables. Indeed, it is well established that the macroeconomic indicators affecting container shipping are not static and can vary (Yin & Shi, 2018). These distinct operational and economic characteristics imply that resilience planning in shipping should account for segment-specific risk exposures and recovery capacities.

Many studies in the literature examine the factors influencing demand across various sectors. However, fluctuations in freight and the resulting demand elasticity should be regarded as a distinct area of research within the context of shipping. Potential decreases in shipping demand may vary in response to economic crises and market fluctuations. In this context, recent years have seen an increase in studies focusing on freight fluctuations in shipping and the corresponding demand variability. Kavussanos and Alizadeh (2001) investigated the impact of seasonality on fluctuations

in dry bulk shipping freight rates. Jugović et al. (2015) evaluated the factors affecting shipping markets based on five fundamental supply and demand variables. Michail (2020) examined the relationship between oil prices and the volume of cargo transported by presenting a maritime trade forecast based on the global economic environment. In a similar line, Mou et al. (2019) assessed the impact of oil prices on tanker transport at the regional level. Nomikos and Tsouknidis (2023) defined independent demand and supply shocks and analyzed their effects on real freight rates and net contract activities. Lun et al. (2013) examined the influence of shipping demand and freight rates on the service capacity of the container shipping industry. Chang et al. (2023) assessed the impacts of the COVID-19 pandemic on international shipping based on BDI. However, most studies treat freight rates and shipping demand fluctuations independently, failing to capture the dynamic interaction between them under uncertainty.

Freight fluctuations and shipping demand variability on a national level are addressed in many studies. Kawasaki et al. (2022), in their research on demand forecasting for container shipping, analyzed the economic indicators that influence the volume of container movements in the United States. They utilized monthly data from 2001 to 2019 and employed the vector autoregression (VAR) method. Özen et al. (2020) conducted a study to determine the impact of commodity groups on road transport in Türkiye. Coto-Millán et al. (2005) evaluated the determinants of international shipping activities in Spain. Iqbal et al. (2024) examined the results of exchange rate fluctuations on commodity trade on the Pakistan-Japan route for the period 1980-2020, considering symmetric and asymmetric effects. Anh et al. (2019) analyzed the relationship between exchange rate fluctuations and trade flows between China and Vietnam using the ARDL method. Sugiharti et al. (2020) examined the impact of exchange rate volatility on Indonesia's primary export goods to five major export destinations. Similarly, Ibrahim et al. (2024) investigated both the symmetric and asymmetric effects of exchange rate volatility, along with other explanatory variables, on 16 food products traded by Indonesia. Khalid et al. (2024) conducted an examination of the effects of exchange rate fluctuations on Turkish-German commodity trade in an asymmetric approach during the period 1980-2022. Aytekin et al. (2024) conducted an analysis using a multi-criteria decision-making method, involving companies operating in the Samsun province of Türkiye, to identify the factors influencing shipping demand management and to develop the most effective strategies.

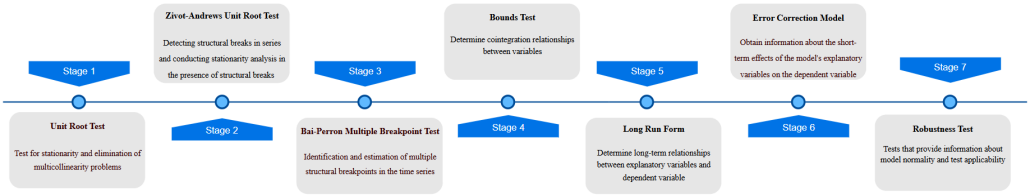
A positive shock in global geopolitical risks leads to an immediate increase in maritime freight rates; however, this effect gradually decreases over time (Drobetz et al., 2021). This assumption reveals the importance of incorporating global risks into country-specific studies. Numerous studies have explored maritime freight rates using the GEPU index, a relatively recent concept in the shipping sector. Gu and Liu (2022) investigated the relationship between maritime freight rates in the dry bulk shipping market and the Chinese manufacturing industry, analyzing the impact of China's GEPU data on freight rates. Aslan & Acikgoz (2023a) examined the effects of the GEPU index on export flows from emerging markets, employing the SVAR method with monthly data for the period from 2003 to 2019. Sun et al. (2024) assessed the relationship between food prices and shipping using the VAR model along with the GEPU index. Furthermore, Aslan & Acikgoz (2023b) also analyzed the effects of GEPU on export flows, using monthly data from 2006 to 2019.

Methodology

In this study, the ARDL model is employed to explore the short- and long-term impacts of GEPU, INPI, BDI, COM, and OIL on the shipping of Türkiye. To do so, first, the ADF unit root test was used to determine the stationarity of the variables in this study. The ARDL model is developed, followed by diagnostic tests. EViews 10 and 12 are used for all data analyses. The methodological framework of the study is presented in Figure 2.

Figure 2

Methodological Framework



The ARDL method is defined as a modeling approach that removes trends when the variables exhibit stationarity in both long- and short-term relationships. ARDL results in consistent estimates for I(1) and I(0) variables (Pesaran & Shin, 1995). This method enhances efficiency by simplifying the analysis, particularly when it is assumed that there is a natural ordering of the variables with no contemporaneous feedback (Kripfganz & Schneider, 2023). The ARDL model facilitates a thorough comprehension of both short- and long-term dynamics within a single reduced-form equation (Daly et al., 2024). In this research, we employ the ARDL model to examine the dynamic relationship between Türkiye's shipping demand (SD), the Global Economic Policy Uncertainty Index (GEPU), the Industrial Production Index (INPI), freight rates (BDI), commodity prices (COM), and crude oil prices (OIL).

$$SD_t = f(INPI_t, BDI_t, GEPU_t, COM_t, OIL_t)$$

The long-run relationship within the ARDL framework is specified as follows:

$$lnSD_t = \alpha_0 + \beta_1 lnINPI_t + \beta_2 lnBDI_t + \beta_3 lnGEPU_t + \beta_4 lnCOM_t + \beta_5 lnOIL_t + \delta_1 D_{2017,\,t} + \delta_2 D_{2019,\,t} + \varepsilon_t$$

ε_t is the error term, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are elasticities, α_0 is the constant term, the dummy variables $D_{2017,t}$and $D_{2019,t}$ that capture structural breaks, δ_1, δ_2 represents the intercept shifts linked to the dummy variables. The ARDL-ECM model is specified as follows:

$$\Delta\, ln\, SD_{\mathrm{t}} = \alpha_{\,0} + \sum_{i=0}^{p_1} \Delta\, ln\, SD_{\mathrm{t\text{-}i}} + \sum_{j=0}^{p_2} \Delta\, ln\, INPI_{t-j} + \sum_{k=0}^{p_3} \Delta\, ln\, BDI_{t-k}$$

$$+ \sum_{l=0}^{p_4} \Delta\, ln\, GEPU_{t-l} + \sum_{m=0}^{p_5} \Delta\, ln\, COM_{t-m} + \sum_{n=0}^{p_6} \Delta\, ln\, OIL_{t-n}$$

$$+ \lambda\, ECT_{\mathrm{t-\,1}} + \delta_{\,1} D_{\,2\,0\,1\,7,\mathrm{t}} + \delta_{\,2} D_{\,2\,0\,1\,9,\mathrm{t}} + \varepsilon_{\mathrm{t}}$$

$^{\mathrm{p}}1, ^{\mathrm{p}}2, ^{\mathrm{p}}3, ^{\mathrm{p}}4, ^{\mathrm{p}}5, ^{\mathrm{p}}6$ denote the optimal lag lengths associated with each variable. ECT_{t-1} is the error correction term derived from the estimated long-run relationship, λ is the error correction coefficient. The symbol Δ denotes the difference operator, t indicates the period, and ln refers to the logarithmic value of the variable.

Data collection and variable selection

This study investigates the short- and long-term relationships between shipping demand and sectoral parameters in Turkish shipping. In this context, the ARDL method was applied using monthly data from 2012 to 2025. The variables used in the study and their sources are presented in Table 1.

Table 1

Details of the Variables Used in the Study

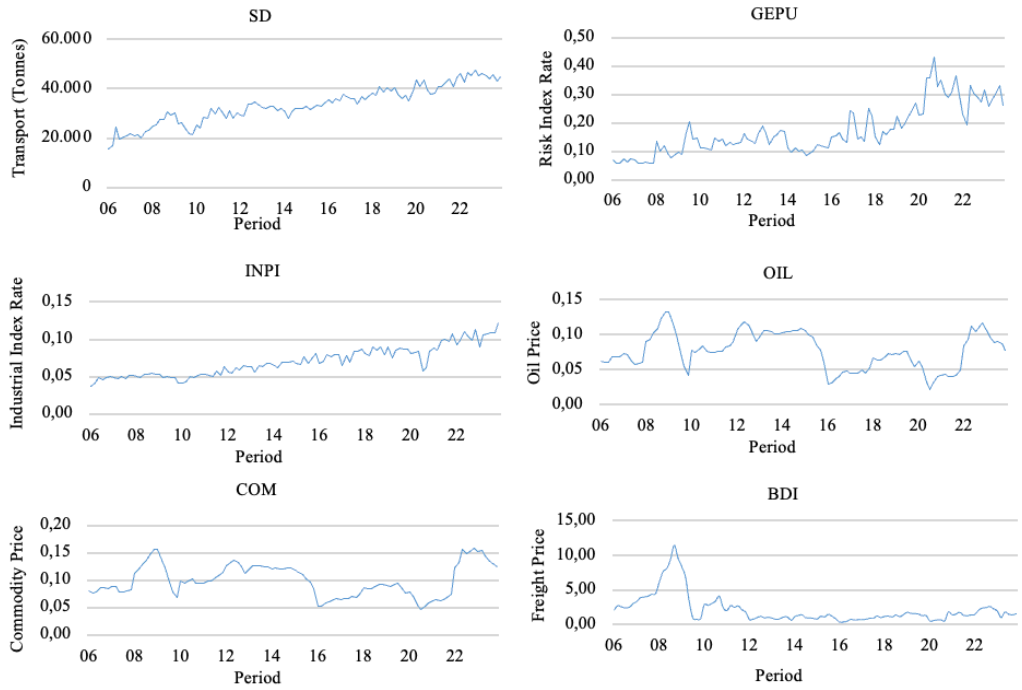
Series	Short Form	Definition	Reference
Shipping Demand	SD	Import, export, and Cabotage Data of the Turkish Shipping Sector (ton)	(Turkish Chamber of Shipping, 2024)
Global Economic Policy Uncertainty Index	GEPU	Economic uncertainty data for 21 countries	(Baker et al., 2024)
Industrial Production Index	INPI	Production capacity index of Türkiye	(TURKSTAT, 2024)

Series	Short Form	Definition	Reference
Freight Rate	BDI	Service Fee for Shipping Index Based on the Baltic Dry Index	(Trading Economics, 2024)
Commodity Price	COM	Commodity prices transported by sea	(Index Mundi, 2024)
Crude Oil	OIL	Price of Crude Oil Used for Shipping Activities	(Index Mundi, 2024)

Notes: Data for the period from January 2012 to June 2025 are included.

Figure 3

Trends of the Used Variables (SD, GEPU, INPI, BDI, COM, and OIL)



Notes: Numerical data are in thousands.

Table 2 presents the descriptive statistics for the variables used in the analysis. Notably, the BDI exhibits a high standard deviation. The ADF stationarity test suggests that all series are either I(0) or I(1); this finding implies that the use of the ARDL model is suitable. Variables were transformed into their natural logarithms to facilitate estimation and reduce the sharpness of the dataset (Murshed, 2021).

Table 2

Descriptive statistics and unit root test results

Statistic	SD	INPI	OIL	BDI	GEPU	COM
Mean	17.468	4.4313	4.2347	7.0781	5.2489	4.5890
Median	17.485	4.4379	4.2808	7.0711	5.2457	4.6141
Maximum	17.711	4.8767	4.7689	8.5500	6.3710	5.1520
Minimum	17.155	3.9963	3.0464	5.7589	4.4616	3.8339
Std. Dev.	0.1362	0.2019	0.3389	0.4879	0.4032	0.3245
Skewness	−0.2670	−0.0876	−0.5501	0.1158	0.1653	−0.0187
Kurtosis	1.9528	2.1068	2.9968	3.1770	2.2673	2.0220
Probability	0.0094	0.0610	0.0168	0.7504	0.1129	0.0394
Observations	162	162	162	162	162	162

ADF-URT (Level)				
	Constant		Constant and Trend	
Variables	Statistics	Probability	Statistics	Probability
lnSD	−0.914018	0.7817	−5.380468	0.0001*
lnINPI	−1.129946	0.7031	−2.124903	0.5274
lnBDI	−3.905943	0.0025*	−4.415199	0.0028*
lnGEPU	−2.294620	0.1750	−4.567486	0.0016*
lnOIL	−2.373947	0.1508	−2.306811	0.4275
lnCOM	−1.428176	0.5673	−1.883780	0.6583

Notes: All variables have been converted to log form. * Significance at the p<0.01 (1% level). ** Significance at the p<0.05 (5% level). *** Significance at the p<0.10 (10% level).

ADF-URT (1st Difference)				
	Constant		Constant and Trend	
Variables	Statistics	Probability	Statistics	Probability
lnSD	−10.38076	0.0000*	−10.34066	0.0000*
lnINPI	−5.814286	0.0000*	−5.842320	0.0000*
lnBDI	−14.50672	0.0000*	−14.46269	0.0000*
lnGEPU	−16.17328	0.0000*	−16.13459	0.0000*
lnOIL	−9.582473	0.0000*	−9.593521	0.0000*
lnCOM	−9.800480	0.0000*	−9.919947	0.0000*

Notes: All variables have been converted to log form. * Significance at the p<0.01 (1% level).

ZIVOT-ANDREWS URT (LEVEL)						
	Constant			Constant and Trend		
Variables	t-Statistics		Break Date	t-Statistics		Break Date
lnSD	−4.599456		2022M11	−4.549412		2022M11
lnINPI	−7.512352		2020M9	−7.700161		2021M8
lnBDI	−5.110801		2020M6	−5.357597		2020M6
lnGEPU	−3.053513		2020M12	−3.139030		2023M4
lnOIL	−4.059418		2014M10	−4.054291		2014M10
lnCOM	−3.565630		2014M9	−3.671370		2014M10
Critical Value	1%	5%	10%	1%	5%	10%
	−5.34	−4.93	−4.58	−5.57	−5.08	−4.82

Notes: All variables have been converted to log form. * Significance at the p<0.01 (1% level). ** Significance at the p<0.05 (5% level). *** Significance at the p<0.10 (10% level).

ZIVOT-ANDREWS URT (1st Difference)				
	Constant		Constant and Trend	
Variables	t-Statistics	Break Date	t-Statistics	Break Date
lnSD	−10.14335	2014M4	−10.55403	2017M9
lnINPI	−9.981147	2020M6	−10.05503	2020M6
lnBDI	−7.453471	2021M10	−7.458090	2021M10
lnGEPU	−10.68793	2020M6	−10.86583	2023M4
lnOIL	−10.01596	2020M5	−10.24353	2020M5
lnCOM	−10.31530	2020M5	−10.41101	2020M5

Critical Value	1%	5%	10%	1%	5%	10%
	−5.34	−4.93	−4.58	−5.57	−5.08	−4.82

Notes: All variables have been converted to log form. * Significance at the p<0.01 (1% level). ** Significance at the p<0.05 (5% level). *** Significance at the p<0.10 (10% level).

The Zivot-Andrews unit root test presented in Table 2 provides information not only on the stationarity properties of the series but also on the presence of structural breaks within the series. The Zivot-Andrews test detects statistically significant structural breaks for INPI on 2021M8 and BDI 2020 M6 at the level, which shows the existence of two break periods in the model when critical values are considered. The disruptions during the 2020 period reflect the effects of the COVID-19 pandemic.

Table 3

Bai-Perron Multiple Breakpoint Test

Break Test	F-statistic	Scaled F-statistic	Critical Value	Break Date
0 vs. 1 *	12.00947	72.05684	20.08	2017M3
1 vs. 2 *	5.842736	35.05641	22.11	2019M3
2 vs. 3	2.967781	17.80669	23.04	-

Notes: In this fracture test, sequential L+1 fracture with L specification was applied. The Bai-Perron test argues that a break occurs when the scaled f statistic value is higher than the critical value. * denotes that the null hypothesis is rejected, indicating statistical significance.

The Bai-Perron approach in Table 3, used in the study to analyze structural breaks, shows the existence of two break periods. According to the test results, two structural breaks covering the periods of March 2017 and March 2019 were detected with significant f-statistics.

Empirical Results

In the following step, the bounds test approach was employed to identify long- and short-run relationships, as presented in Table 4. The optimal lag length in the ARDL model was selected based on the Akaike Information Criterion, which indicated a maximum lag length of four.

Table 4

ARDL boundary test

Long-Term			
F-Statistics	Significance	I(0) Lower Bound	I(1) Upper Bound
3.738586	10%	1.95	3.06
	5%	2.22	3.39
	2.5%	2.48	3.70
	1%	2.79	4.10

Notes: Null Hypothesis no long-run relationships exist.

According to the results of the long-term bounds test in Table 4, the F-statistic value exceeds the upper critical values at the 5% significance level. Consequently, it was determined that the variables included in the model exhibit a long-term co-integration relationship with one another.

Table 5

Error Correction Model and Long Run Forms ARDL Model

Model	Coefficient	Std. Error	t-Statistic	Prob.
ARDL (2, 4, 4, 2, 4, 0, 0, 1)				
ECM				
C	6.119665	1.053175	5.810683	0.0000
Δ(lnSD(-1))	−0.364771	0.068845	−5.298424	0.0000
Δ(lnINPI)	0.277709	0.033536	8.280909	0.0000
Δ(lnINPI(-1))	0.092760	0.047920	1.935713	0.0550
Δ(lnINPI(-2))	−0.123147	0.040566	−3.035736	0.0029
Δ(lnINPI(-3))	−0.068520	0.035178	−1.947783	0.0535
Δ(lnOIL)	−0.041906	0.033552	−1.248986	0.2139
Δ(lnOIL(-1))	0.009504	0.037558	0.253044	0.8006
Δ(lnOIL(-2))	0.084698	0.038170	2.218976	0.0282
Δ(lnOIL(-3))	0.065187	0.037385	1.743649	0.0835
Δ(lnBDI)	−0.048717	0.012241	−3.979760	0.0001
Δ(lnBDI(-1))	0.025287	0.013613	1.857527	0.0654
Δ(lnGEPU)	−0.024477	0.017218	−1.421544	0.1575
Δ(lnGEPU(-1))	−0.040825	0.017026	−2.397804	0.0179
Δ(lnGEPU(-2))	−0.023748	0.016967	−1.399687	0.1639
Δ(lnGEPU(-3))	−0.035084	0.016380	−2.141887	0.0340
Δ(dm2)	0.120209	0.028688	4.190197	0.0001
CointEq(-1)*	−0.408145	0.070273	−5.808032	0.0000
R-squared	0.722537			
Adj. R-squared	0.688845			
F-statistic	21.44542			
Prob(F-statistic)	0.000000			
Long Run Forms				
lnINPI	0.527129	0.077426	6.808175	0.0000*
lnOIL	−0.152346	0.062422	−2.440573	0.0160**
lnBDI	−0.007479	0.025953	−0.288157	0.7737
lnGEPU	0.051186	0.031090	1.646374	0.1020
lnCOM	0.123381	0.062880	1.962176	0.0518***
dm1	0.029259	0.032576	0.898178	0.3707
dm2	0.083697	0.031594	2.649094	0.0090*
Diagnostics Tests	Prob. F.	F-Statistic	Prob. Chi-Square	Obs*R-Squared
Breusch-Godfrey Serial Correlation LM Test	0.7959	0.228666	0.7597	0.549672
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.1281	1.380761	0.1395	31.51498
Ramsey Reset Test	0.2406	1.389508	-	-
Normality Test	0.5526	-	-	-

Notes: *significance at 1%, ** 5%, *** 10% at the level. Diagnostic tests are considered significant at a 0.05 < p-value level. “d” denotes the first-order difference.

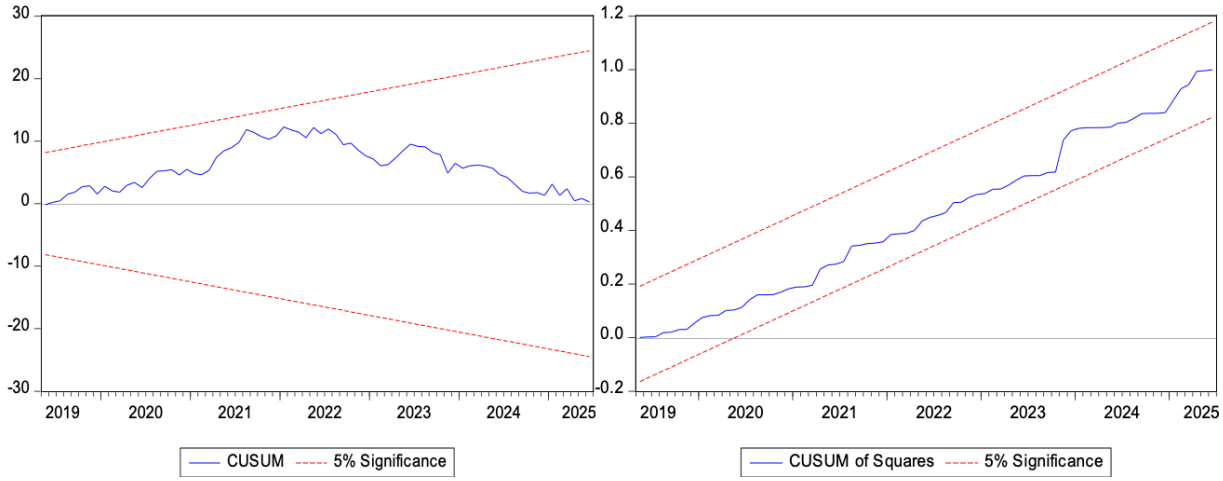
The ARDL model used in the study is based on a constant specification to account for periodic deviations within the equilibrium framework. The lag length of the model is determined using the Akaike Information Criterion. The commonly accepted upper limit of four lags is adopted to capture both short- and long-term effects. The long-run estimation results indicate that INPI has a positive and statistically significant effect on shipping demand ($\beta = 0.5271$, $p < 0.01$). Specifically, a 1% increase in industrial production is associated with a 0.52% increase in shipping demand eventually. In contrast, OIL exhibits a negative and statistically significant long-run relationship with shipping demand ($\beta = -0.1523$, $p < 0.05$), suggesting that higher energy costs may exert downward pressure on shipping activity. The structural dummy for March 2019 (dm2) is positive and statistically significant ($\beta = 0.0837$, $p < 0.01$), indicating that the post-2019 period is associated with a persistent upward shift in shipping demand and suggesting a regime change in the underlying market structure. Furthermore, COM exhibits a positive but weak long-run relationship with shipping demand ($\beta = 0.1234$, $p < 0.10$), as the coefficient is only marginally significant at the 10% level.

The short-run estimation results show that INPI exerts a positive and statistically significant effect on shipping demand ($\beta = 0.2777$, $p < 0.01$). Several lagged changes in industrial production are also significant, reflecting short-run persistence in the impact of industrial activity. Short-run changes in OIL exhibit mixed effects. While the contemporaneous and first lagged coefficients are insignificant, the second lag is positive and significant ($\beta = 0.0847$, $p < 0.05$), indicating delayed adjustment effects in the shipping market. Changes in the BDI have a negative and significant contemporaneous impact on shipping demand ($\beta = -0.0487$, $p < 0.01$), whereas the lagged effect is only marginally significant. GEPU displays predominantly negative short-run effects, with the first and third lags being statistically significant ($\beta = -0.0408$ and $\beta = -0.0351$, respectively), suggesting that heightened uncertainty suppresses shipping demand in the short run. Finally, the short-run structural dummy for March 2019 is positive and statistically significant ($\beta = 0.1202$, $p < 0.01$) in the short term, indicating that an immediate upward shift in shipping demand during these key years had both immediate and lasting effects. The error correction term (CointEq(-1) = −0.4081, $p < 0.01$) carries the expected negative sign, confirming a stable long-run relationship among the variables. Approximately 40% of the previous month's disequilibrium is corrected within 1 month, indicating a relatively fast adjustment process toward long-run equilibrium. The Ramsey RESET test confirmed that there is no functional form misspecification in the model. Furthermore, the results of the diagnostic tests showed no issues regarding the assumptions of heteroscedasticity, autocorrelation, and normality.

Overall, the results confirm the existence of long- and short-run relationships among SD, INPI, oil, COM, and GEPU. The ARDL-ECM findings show that deviations from the long-run equilibrium are corrected relatively quickly, as reflected by the statistically significant CointEq(-1) term. The inclusion of the structural break dummy dm2 (March 2019) captures a significant regime shift, suggesting a persistent change in the SD level after this period. These findings highlight that macroeconomic conditions are key determinants of long-term stability and short-term responsiveness in Türkiye's shipping industry.

Figure 4

Cusum and Cusum of Squares Tests



According to the results of the CUSUM and CUSUM square tests in Figure 4, the variables in the model exhibit a normal distribution. Variables that fall within the critical limits at the 5% significance level suggest that there is no structural change in the model.

Discussion and Sectoral Recommendations

Shipping industry is a vital part of international trade and a key factor in the sustainable development of our global economy. Because a large proportion of global freight is transported by sea, it is essential to have an accurate understanding of how shipping demand evolves within the maritime sector for economic development and planning. Changes in the amount of shipping demand can have negative effects on this sector. Factors such as the global economy's performance, fluctuations in freight rates, and political uncertainty create changes in the shipping market that will upset the groundwork for balancing supply and demand. Identifying the structural trends illustrated in Figure 3 within the shipping sector will assist policymakers in developing effective strategies for its development. Previous studies that analyze how different macroeconomic variables influence shipping demand emphasize their importance on both individual sectoral growth and overall stability of the shipping sector (Chang et al., 2023; Coto-Millán et al., 2005; Kawasaki et al., 2022; Nomikos & Tsouknidis, 2023).

Türkiye plays a decisive role in the generalizability of structural trends due to its unique geographical position, being surrounded by seas on three sides and situated along a strategic logistics corridor. The aim of the current study is to identify the factors influencing shipping demand in Türkiye. The ARDL model used in the analysis of monthly data from 2012 to 2025 revealed the primary causes of sectoral fluctuations by examining relationships among the variables.

The findings revealed significant effects of industrial activity on the sector. Specifically, a positive and significant relationship was identified between shipping demand and INPI. This positive correlation supports existing literature (Ibrahim et al., 2024; Sugiharti et al., 2020). The relationship between the INPI and shipping demand demonstrates that increases in production capacity led to increased demand for shipping activities, indicating a directly proportional relationship. In this regard, the establishment of a data-driven coordination framework between shipping demands and industrial production trends may enhance long-term resilience. To operationalize this, we recommend the development of predictive analytics tools to anticipate demand shifts under uncertainty and the establishment of in-house data science departments to support real-time decision-making. Furthermore, the adoption of adaptive business models, such as demand-responsive chartering, can enhance operational flexibility in volatile markets.

The negative and statistically significant impact of crude oil on shipping demand in the long term presents an economically consistent outcome within the framework of the sector's cost structure and investment dynamics. This negative effect is well supported by literature, both in terms of long-term structural impacts (Michail, 2020) and short-term market responses to price slumps (Mou et al., 2019). Fuel costs constitute one of the most important components of operating costs in maritime transport. An increase in the OIL variable directly raises vessel operating costs through fuel prices and increases unit costs per shipment.

Using Bai-Perron analysis, March 2019 revealed a clear breakpoint (dm2); during both time horizons, this variable was statistically significant (1% threshold), indicating that domestic demand will skip temporary spikes and settle into a permanently new regime. The sectoral records back this up. Export data show that the volume of maritime trade was on a steady upward trend from 2017 until the last quarter of 2019 (Öçal, 2022). To meet this demand, operators scaled their physical capacity to handle goods. The large amount of physical expansion that occurred prior to this underpinned how well these operations absorbed any macro-shocks. When the pandemic-related lockdowns disrupted supply chains globally within months afterwards, Turkish terminals used this accumulated baseline to clear their backlog of containers. They finished 2020 with record levels of cargo volume achieved. This performance negotiated the contraction before it could inflict systemic-wide harm (MTI-GDMA, 2021a, 2021b). Authorities may use these types of mathematical shifts to help determine when to track the physical expansions of maritime infrastructure limits over time.

In addition to reinforcing how these outcomes exhibit resilience by helping to buffer the negative impacts of either unexpected market shocks or dispersed policy changes, the results also provide evidence that the sector demonstrates practical adaptive capabilities rather than just theoretical ones. This is evident from the relatively rapid adjustment that occurs (about 40% per month) toward long-term equilibrium after being subject to disruption. As a result, national maritime policies should include resilience protocols related to integrating seaport logistics centers, especially during periods of crisis, shock, fluctuation, or conflict, to ensure uninterrupted service during times of significant uncertainty.

The long term also shows a lack of statistical significance between freight rate and shipping demand as per estimations completed using the ARDL model but demonstrated that the short term showed a statistically significant and negative relationship between the two. Shippers and the entire supply chain can expect freight rates to increase as demand for container shipping increases, and if demand decreases, carriers will reposition their fleet to another shipping service. The container shipping industry can adopt hybrid pricing structures, which typically include both long-term stable contracts while providing a mechanism for adjusting short-term rates to improve their ability to react to sudden changes in shipping demand, resulting in improved commercial resiliency within the industry.

Conclusion

This study examined the macroeconomic determinants of aggregate shipping demand in Türkiye using monthly data and an ARDL-ECM specification that incorporates structural break dummies. Industrial production and energy costs are the statistically significant long-run determinants, with commodity prices marginally so. The freight market conditions and global uncertainty appear to have no long-lasting equilibrium relationship with shipping demand; however, they do produce negative impacts on shipping demand with various lagging effects in the short term. This suggests that these variables are transmitting short-term shocks to the shipping industry rather than permanently adjusting to a new structure. The March 2019 structural break is the only Bai-Perron-identified break that reaches statistical significance in the long-run estimates; it predates the COVID-19 period. This study makes three contributions to the shipping demand literature. First, to the authors' knowledge, an ARDL-ECM framework with structural break dummies has not previously been applied to Turkish aggregate shipping demand using monthly data. Second, to the authors' knowledge, the divergence between the long-run insignificance and short-run significance of GEPU and BDI has not been tested within a national shipping demand framework. Third, the statistically significant regime shift in March 2019 cannot be attributed to pandemic-related disruptions; its proximate drivers remain an open empirical question.

Limitations and recommendations for future research

There were limitations in this study. The study did not consider gross domestic product and gross value-added variables due to data limitations. The research focused on macro-scale variables. Analyzing the difference in shipping demand by cargo and vessel types will assist in understanding microdynamics in the industry. The models and data used in this study produced results for the current period; however, they limit forecasting for the future. Future research should explore the use of machine learning and artificial intelligence-based models to enhance the accuracy of long-term shipping demand forecasts.

Typically, national economic policies and political strategies affect commercial activities in one form or another. If we identify the core factors that determine shipping demand, we can develop the shipping industry by executing operations efficiently and effectively. It is essential for maritime authorities in Türkiye to develop comprehensive plans that include the GEPU index and INPI variables so that the shipping industry can create successful strategies for dealing with the global shocks facing the sector now and in the future. Future research will help better understand how global economies influence investment decisions for shipping and provide insight into how economic indicators influence maritime freight rates. Findings related to risk management will be developed by subsequent studies of the sector.

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