Journal of Shipping and Trade

ORIGINAL ARTICLE Open Access

Mean reversion and long memory dynamics in the Shanghai Containerized Freight Index

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Abstract

This paper deals with the investigation of the long memory properties of the Shanghai Containerized Freight Index for the time period from 16 October 2009 to 18 October 2024. Using fractional integration methods, we want to determine if shocks in the series have transitory or permanent effects. The results indicate that the series are very persistent when using the whole sample size with an order of integration above 1. However, if we separate three different subsamples, corresponding to the pre-Covid, Covid and post-Covid periods, we observe reversion to the mean in the pre-Covid period; however, during the Covid, there is a substantial increase in the value of d and turns decreasing after the pandemic.

Keywords: Shanghai Containerized Freight Index, Long memory, Persistence, Fractional integration, Covid-19

JEL Classification: C22; B17; R41

Introduction

Maritime transport serves as the backbone of global trade acting as the primary conduit through which goods are exchanged across continents (See Fig. 1). In 2023, the volume of goods transported by sea reached 12,292 million tons, accounting for approximately 80% of global trade by volume and over 50% by value (UNCTAD 2022, 2024). However, the sector is currently facing a range of challenges that threaten its reliability and efficiency. Given the absence of viable alternatives for moving such large quantities of cargo, increases in maritime transport costs inevitably lead to higher shipping rates. These costs cascade through supply chains, contributing to increased consumer prices, heightened inflation, and ultimately, hindering global economic growth.

Notably, the heavy reliance on chokepoints—strategic narrow maritime passages—remains one of the key characteristics of seaborne transport, making it especially vulnerable to disruptions. Recent events have underscored the fragility of the maritime transport network and its intricate balance. For instance, the 2021 blockage of the Suez Canal by the *Ever Given*, the reduced water levels in the Panama Canal due to the 2023 drought, and Houthi attacks on ships crossing the Red Sea and the Suez Canal since late 2023 all serve as stark reminders of how such disruptions can lead to extended shipping routes and increased operational costs. In contrast, the disruption

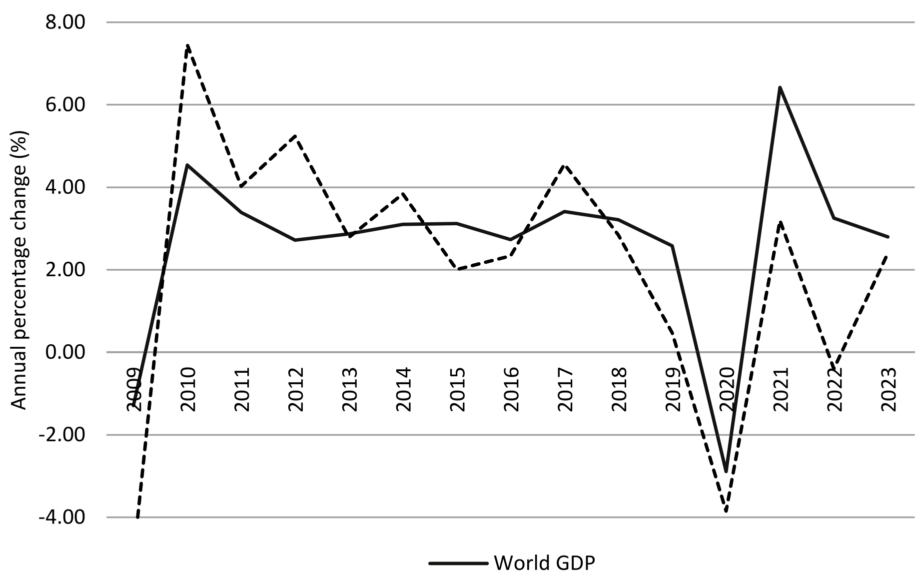

Fig. 1 Growth of world GDP and international maritime trade. *Source* UNCTAD. Real GDP growth and seaborne trade figures (total loaded goods). Own elaboration

caused by the exogenous shock of the COVID-19 pandemic was fundamentally different, as it originated from a slowdown in global manufacturing and trade, which subsequently affected the demand for maritime transport.

The main objective of this article is to analyze the long-term statistical behavior of maritime transport costs at Shanghai Port and to understand how these costs evolve following disruptive events. We have chosen Shanghai Port for this study because it is the world's largest container port, exceeding 47.4 million TEUs (UNCTAD 2023). Specifically, this research examines the statistical properties of the Shanghai Containerized Freight Index (SCFI), measuring the degree of persistence through fractional integration techniques. If the index demonstrated mean reversion, it would suggest that costs are likely to recover their original trend once the effects of the exogenous shock have dissipated, thereby facilitating the recovery of economic activity. Conversely, if long-term persistence of shocks is observed, it would indicate that the effects of disruptions may have more lasting consequences.

Anticipating the results, the series shows a high degree of persistence when looking at the whole sample size that runs from 16 October 2009 to 18 October 2024; however, if we separate it in three subsamples corresponding to pre-Covid19 pandemia, the Covid19, and the post-Covid pandemia, we observe that the degree of persistence substantially increased during the health crisis period moving from mean reversion in the pre-Covid19 period to lack of it afterwards.

As for the structure of the article, after this introductory section, a brief review of the most relevant literature on the subject of analysis is presented. Next, in Sect. "Data and methodology", the data and methodology used in the research are detailed, and then, in Sect. "Empirical results", the main results of the analysis are presented. The article concludes with the main findings of this research.

Literature review

Due to its significant importance, maritime transport has been the subject of extensive academic research (Goulielmos 2018, 2019; Ke et al. 2024). A considerable number of studies have examined key factors influencing maritime freight rates, focusing on specific characteristics such as the distance between ports (Deuss et al. 2022), shortages of empty containers (Toygar et al. 2022), port congestion (Michail & Melas 2025), and the size of importing firms (Ardelean & Lugovskyy 2023). Other research has explored the impact of broader factors, including the macroeconomic environment, geopolitical risk, and oil prices (Michail 2020; Siddiqui & Basu 2020; Khan et al. 2021; Chen et al. 2024), as well as the effects of exogenous shocks such as the Covid-19 pandemic (Michail & Melas 2020, 2022).

Another substantial branch of the literature has examined the volatility of tanker freight rates and their relationship with uncertainty and oil prices (Kavussanos & Alizadeh-M, 2001; Chou 2016; Ruan et al. 2016; Thanopoulou & Strandenes 2017; Li et al. 2018; Bai 2021; Monge et al. 2023; Tiwari et al. 2024; etc.). Researchers have also explored the macroeconomic impacts of surges in maritime freight rates, finding that such increases lead to higher import prices and inflation, while reversing trends toward globalization and encouraging a shift toward localization (Ding & Wang 2022; UNCTAD 2022; Carrière-Swallow et al. 2023; Carter et al. 2023; Ferrari et al. 2023). Additionally, various time-series models, deep learning techniques, and other advanced analytical approaches have been employed to forecast the evolution of freight rates (Koyuncu & Tavacioğlu 2021; Hirata & Matsuda 2022; Munim 2022; Tu et al. 2023).

Instead, less attention has been devoted to the long memory and mean reversion characteristics of maritime freight rates, despite their critical importance to the sector. Ding et al. (2018) investigated structural breaks and long memory features across different vessel sizes. The study employs the Multifractal Detrended Fluctuation Analysis (MF-DFA) method, an extension of the Detrended Fluctuation Analysis (DFA), which is suitable for both stationary and non-stationary time series. Its main advantage lies in its ability to effectively remove trend components and detect long-range correlations. To identify structural breakpoints, the source applies the ICSS (Iterated Cumulative Sum of Squares) algorithm, which detects sudden changes in variance under the assumption that volatility remains stationary between breaks. They find that the presence of long memory implies that past shocks exert persistent effects on current freight rates.

Xu et al. (2021) analyzed the long memory properties of the Panamax and Handy-size carrier markets, concluding that both sub-markets exhibit long memory behavior. This paper employs Rescaled Range (R/S) Analysis, Modified R/S Analysis, and the V-statistic (V/S) test of Giraitis et al. (2003). The R/S and Modified R/S methods are classical approaches based on the works of Hurst (1951) and Lo (1991), respectively, aimed at estimating the Hurst exponent (H), which quantifies the degree of persistence in time series. The Modified R/S Analysis, introduced by Lo (1991), enhances the classical R/S method by improving its robustness in the presence of heteroskedasticity, non-stationarity, or short-term memory, thus aiding in the distinction between short- and long-range dependence.

Interestingly, Hayashi (2020) found that while the freight rate process itself is non-stationary and therefore not mean-reverting, the deviation of freight rates from estimates

Table 1 Main descriptive statistics of the full sample and sub-samples *Source* UNCTAD. SCFI Composite Index. Own Elaboration

	N observations	Mean	Standard Deviation	Max	Min
Full Sample October 16, 2009–October 18, 2024	752	1,426.14	1,060.96	5,109.60	400.43
Pre-Covid Subsample October 16, 2009–March 6, 2020	517	958.57	242.68	1,583.18	400.43
Post-Covid Subsample March 13, 2009–October 18, 2020	235	2,454.81	1,391.77	5,109.60	818.16

based on the demand/supply ratio is stationary and mean-reverting. The primary methodology employed is the Augmented Dickey-Fuller (ADF, Dickey and Fuller 1979) test to assess stationarity by detecting the presence of a unit root. In addition, a first-order Autoregressive model (AR(1)) is applied to quantify the strength of mean reversion through the autoregressive coefficient.

In the shipping industry, it is widely assumed that freight rates are determined by supply and demand in the long run, and that any short-term deviations will gradually diminish over time. However, empirical studies frequently find that freight rate processes are non-stationary, challenging the assumption of mean reversion. This paper contributes to the existing literature by providing a detailed analysis of the long-term statistical behavior of the SCFI. As this index is a key indicator of global economic activity, understanding its fluctuations is essential for effective supply chain management and the formulation of public policies aimed at mitigating adverse impacts.

Data and methodology

The main objective of this paper is to determine whether the costs of the most relevant world maritime transport port exhibit persistent deviations from equilibrium through fractional integration techniques. For this purpose, we analyze weekly data from the Shanghai Containerized Freight Index (SCFI) spanning from October 16, 2009, to October 18, 2024, resulting in a sample of 752 observations, which is sufficient for the analysis of fractional integration. (See Table 1). Unlike the more comprehensive China Containerized Freight Index data (CCFI), the SCFI excludes long-term contract prices, offering a more detailed view of short-term market fluctuations. As a result, it is particularly sensitive to immediate supply and demand dynamics.

More specifically, we focus on the SCFI Composite index, which is a weighted average of 15 individual routes.[1] Each route reflects the export container market from Shanghai, based on average spot freight rates at the port-to-port level.[2] One of the key advantages of the SCFI is that it is published weekly by the Shanghai Shipping Exchange (SSE). The high-frequency data enables the observation of short-term

[1] The composition of the SCFI has experienced some changes since it was launched on October 16, 2009. Initially it included 13 individual shipping routes, and in June 2017 the Shanghai Shipping Exchange announced the removal of the Hong Kong and Taiwan routes.

[2] The ports of destination are the base ports of the route, e.g. Mediterranean Sea—Barcelona/Valencia/Genoa/Naples, Europe—Hamburg/Rotterdam/Antwerp/Felixstowe/Le Havre, USWC—Los Angeles/Long Beach/Oakland, USEC—New York/Savannah/Norfolk/Charleston, West Japan—Osaka/Kobe, East Japan—Tokyo/Yokohama. The freight rate of individual routes of SCFI is the average all-in price which considers the spot ocean freights and related seaborne surcharges.

volatility and the identification of potential long memory patterns within spot rate movements. Moreover, the SCFI is widely recognized as a reliable and transparent indicator of spot freight rates from Shanghai to major global ports and is used as the underlying asset for freight derivatives, particularly the Shanghai Containerized Freight Index Futures.

The SCFI reacts rapidly to immediate changes in supply and demand, geopolitical shocks, fuel prices fluctuations, and other short-term market signals, making it a useful candidate for statistical tests on persistence and mean reversion. However, for a proper interpretation of the results, it is important to recognize that the index is inherently more volatile and may reflect short-term noise. Furthermore, as the SCFI focuses exclusively on Shanghai as the export port and includes only selected trade routes, the use of this index may limit the generalizability of the findings to broader global maritime market trends.

The evolution shows that the range of index values surged following the outbreak of the Covid-19 pandemic (See Fig. 2). Until March 2020, the index ranged from a peak of 1,583 points in July 2010, driven by rising exports and limited vessel supply, to a low of 400 points in March 2016, due to weaker demand and the introduction of larger container ships in 2015 (UNCTAD 2011, 2016).

However, in the pre-Covid period several events disrupted the global economy, affecting international trade, seaborne trade, and the SCFI (See Fig. 3). First, after the major global financial crisis in 2007–2009, there was a boom in exports and international seaborne particularly relevant in 2010, when the volume of merchandise trade grew at a rate of 16.2% and seaborne trade more than 7% (UNCTAD 2011).

Between 2011 and 2014, the global economy and international trade grew at moderate rates (2–4%), with no major events disrupting the seaborne trade market. However, the SCFI surged in the first half of 2012, primarily due to major container shipping lines implementing General Rate Increases (GRIs) and coordinating

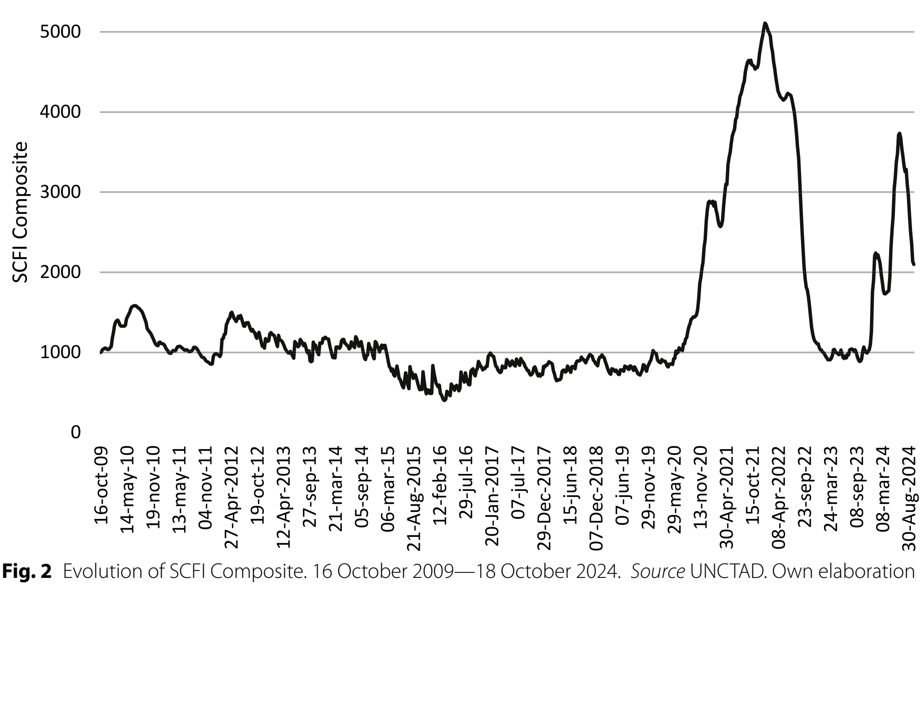

Fig. 2 Evolution of SCFI Composite. 16 October 2009—18 October 2024. *Source* UNCTAD. Own elaboration

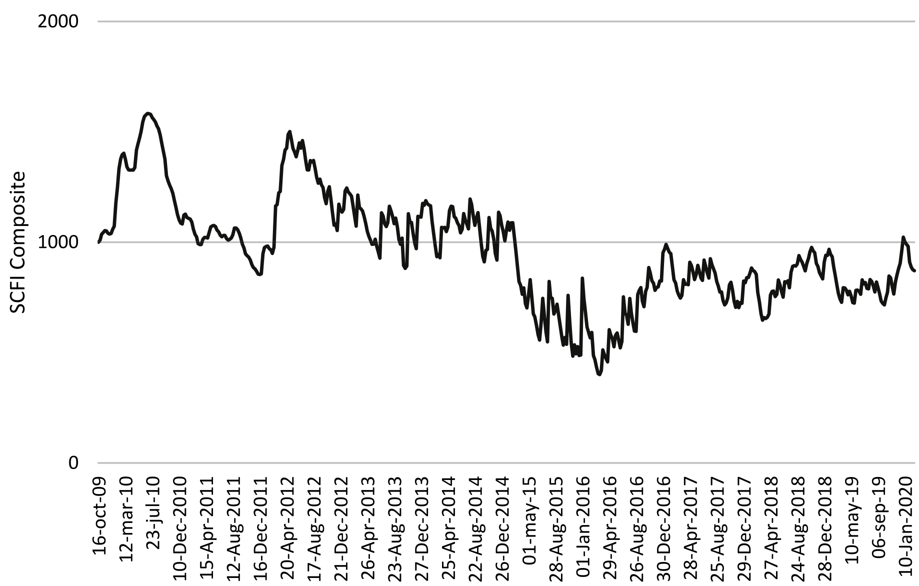

Fig. 3 Evolution of SCFI Composite. 16 October 2009—6 March 2020. *Source* UNCTAD. Own elaboration

capacity management strategies—such as idling ships and blank sailings—to counteract declining freight rates caused by overcapacity (UNCTAD 2011, 2012, 2013, 2014).

In 2015, weak international demand, particularly from China, and an oversupply of tonnage—driven by the introduction of Ultra Large Container Ships (ULCS)— in most shipping segments, except for tankers, triggered historic low levels of freight rates, and in 2016 further decline was mainly due to poor supply side management by operators in face of weak volume growth. The SCFI reached a minimum of 400.43 points the week of March 18, 2016, but adjustments in supply, combined with renewed demand led to market recovery in the second half of the year (UNCTAD 2015, 2016).

In 2017, the improvement in the global economic environment reflected in a strong development in global container shipping demand, but in 2018 international maritime trade lost momentum as a consequence of lower economic growth. In the second half of the year, tariff escalation between China and the United States dominated the headlines, and in anticipation of originally planned January 1, 2019 tariff hikes, many U.S. importers front-loaded goods in the last quarter of the year. Then, as a temporary tariff truce was agreed upon in December 2018, the front-loading of cargoes continued in the initial part of 2019 until, finally, in May 10, 2019, the U.S. increased tariffs from 10 to 25% on $200 billion worth of Chinese goods (UNCTAD 2017, 2018, 2019).

Coherently with these events, we have divided the data series corresponding to the pre-Covid period in the following sub-periods for a more detailed analysis:

(1) Post-crisis boom: October 16, 2009 – December 31, 2010 (N = 55 observations).
(2) Moderate growth (1): January 7, 2011 – December 30, 2012 (N = 50 observations)
(3) Overcapacity management: January 6, 2012 – May 25, 2012 (N = 20 observations)
(4) Moderate growth (2): June 1, 2012 – December 26, 2014 (N = 131 observations)
(5) Oversupply crisis: January 2, 2015 – May 27, 2016 (N = 72 observations).

(6) Moderate growth (3): June 3, 2016 – September 28, 2018 (N = 120 observations).
(7) Tariff hikes anticipation: October 12, 2018 – May 10, 2019 (N = 29 observations).
(8) Moderate growth (4): May 17, 2019 – March 6, 2020 (N = 40 observations).

In March 2020, the outbreak of the coronavirus pandemic caused a sharp decline in demand for seaborne transport (See Fig. 4). To adjust supply, carriers implemented strategies such as increased blank sailings and the idling of vessels, which helped keep freight rates relatively stable. Then, in the second half of 2020, demand rebounded, and container shortages combined with port congestion led to a sharp increase in container freight rates, particularly on routes from China to Europe and the United States (UNCTAD 2020, 2021).

In 2021, the shortage of shipping capacity and ongoing disruptions caused by Covid-19, combined with a rebound in trade volumes, pushed container freight rates to record highs (UNCTAD 2021, 2022). Rates surged further in March 2021 after the Ever Given blocked the Suez Canal, disrupting global trade. Some voyages had to be re-routed around the Cape of Good Hope, and the SCFI peaked at 5,067 points in January 2022 (UNCTAD 2021, 2022). In early 2022, the Russian invasion of Ukraine and the resulting economic sanctions undermined global business confidence. By mid-2022, capacity constraints had eased, and spot freight rates neared pre-COVID-19 levels by year-end (UNCTAD 2023).

The SCFI remained stable in 2023, but container freight rates surged again in 2024 due to an El Niño-induced drought that reduced Panama Canal capacity, forcing carriers to reroute via the Suez Canal, the Strait of Magellan, and the Cape of Good Hope (UNCTAD 2023, 2024). Disruptions in the Red Sea and the Suez Canal further exacerbated congestion at major ports in Asia and the Middle East. In the second half of 2024, tensions eased, and by October 18, the SCFI had dropped 45% from its peak.

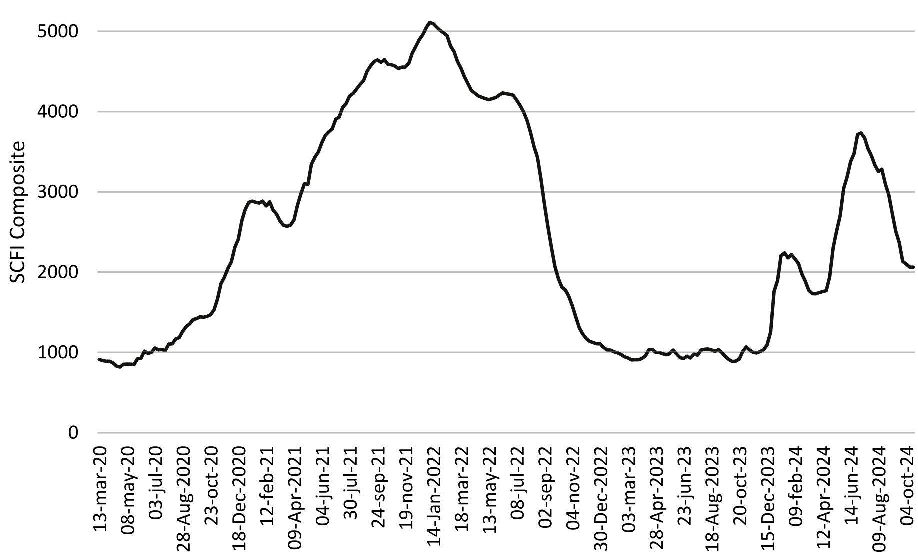

Fig. 4 Evolution of SCFI Composite. 13 March 2020—18 October 2024. *Source* UNCTAD. Own elaboration

For the methodology, we use fractional integration, which is a particular model within the category of long memory processes, and which are characterized by a high degree of dependence between observations even if they are far apart in time. Fractional integration indicates that the number of differencing required in a series to render it stationary I(0) is a non-integer value. Thus, allowing the order of integration to be fractional we allow for a richer and more flexible way in the dynamic specification of the model, which is specified by Eq. (1) below. Granger (1980) adopted this model based on the fact that the estimated spectral density function of many aggregated data displayed a large value at the smallest (zero) frequency suggesting the need of first differentiation; however, doing the same on the differenced series, the estimated spectrum showed a value close to zero at such a frequency, which may indicate overdifferentiation (see, e.g., Granger and Joyeux 1980; Hosking 1981; etc.).[3]

The estimation is conducted via Robinson (1994), a testing procedure that is based on the Lagrange Multiplier (LM) principle and that does not require stationarity for its implementation. In this paper we use a very simple version of this testing procedure, which functional form can be found, for example, in Gil-Alana and Robinson (1994).

Empirical results

The specified model under examination is:

$$y_t = \alpha + \beta t + x_t,\ (1 - L)^d x_t = u_t,\ t = 1, 2, 3, \ldots, T \tag{1}$$

where y_t is the variable of interest (original and in logs), and u_t is supposed to be first a white noise (uncorrelated) process and then, autocorrelated with the model of Bloomfield (1973). As usual, we consider the three cases of i) no deterministic terms, ii) an intercept, and iii) an intercept with a linear time trend, marking in bold the selected case for each model for the disturbances.

We first consider the data, using the whole sample size. Then, we focus on three different subsamples, pre-Covid, Covid, and post-Covid data. We set 11 March 2020 as the start and 5 May 2023 as the end of the pandemic respectively (Ashraf 2021; Coskun et al. 2023), since the former is the date when the World Health Organisation (WHO) characterised the outbreak as a pandemic and the latter is the date when it declared the end to Covid-19 as a global health emergency. These breaks are justified by the change that the pandemia produced all over the world. We could alternatively have estimated the break dates, but we believe that this is not required in this case based on the importance that the pandemic had on the transport industry.

Results using the whole sample period

The results are reported across Tables 2 and 3 for the original data, and in Tables 4 and 5 for the logged values. Starting with the original data, we see in Table 2 that the time trend coefficient is found to be statistically insignificant in the two cases. Thus, we choose the model with only an intercept. It can be observed that the estimate of d is equal to 1.38 in the model with white noise errors and 1.44 with autocorrelation,

[3] See Gil-Alana and Hualde (2009) and Hualde and Nielsen (2023) for reviews of theoretical and applied issues related with fractional integration.

Table 2 Estimates of d. Original data

Type of disturbances	No terms	With an intercept	With an intercept and a time trend
White noise	1.31 (1.26, 1.37)	**1.38 (1.33, 1.44)**	1.38 (1.33, 1.44)
Autocorrelated	1.35 (1.26, 1.47)	**1.44 (1.33, 1.57)**	1.44 (1.33, 1.57)

Values in bold indicate the selected specificiation in relation with the deterministic terms. The values refer to the estimates of d, and in parenthesis, their associated 95% confidence bands

Table 3 Estimated coefficients in the selected models. Original data

Type of disturbances	Diff. par. (95% band)	Intercept (t-value)	Time trend (t-value)
White noise	1.38 (1.33, 1.44)	994.26 (17.48)	---
Autocorrelated	1.44 (1.33, 1.57)	992.45 (3.63)	---

Column 2 indicates the estimate of d and in parenthesis the 95% confidence band for the values of d; column 3 reports the intercept and its associated t-value (in parenthesis); --- indicates lack of statistical significancy

Table 4 Estimates of d. Logged data

Type of disturbances	No terms	With an intercept	With an intercept and a time trend
White noise	1.00 (0.95, 1.06)	**1.09 (1.04, 1.15)**	1.09 (1.04, 1.15)
Autocorrelated	0.98 (0.91, 1.07)	**1.06 (0.99, 1.15)**	1.06 (0.99, 1.15)

Values in bold indicate the selected specificiation in relation with the deterministic terms. The values refer to the estimates of d, and in parenthesis, their associated 95% confidence bands

Table 5 Estimated coefficients in the selected models. Logged data

Type of disturbances	diff. par. (95% band)	Intercept (t-value)	Time trend (t-value)
White noise	1.09 (1.04, 1.15)	6.904 (115.86)	---
Autocorrelated	1.06 (0.99, 1.15)	6.905 (115.55)	---

Column 2 indicates the estimate of d and in parenthesis the 95% confidence band for the values of d; column 3 reports the intercept and its associated t-value (in parenthesis); --- indicates lack of statistical significancy. MR indicates mean reversion

and the unit root null hypothesis, i.e., $d=1$ is rejected in the two cases in favour of values of d above 1. The estimates of the intercept corresponding to these cases are reported in Table 3.

Tables 4 and 5 reports the same estimates but for the logged transformed values. The values are much lower than with the original data. Once again the time trend is unrequired, and the estimates of d are now 1.09 for the model with white noise errors and 1.06 for the model of Bloomfield (1973). It is also noted that for the former model (white noise errors) the unit root null is definitely rejected; however, if autocorrelation is permitted this I(1) hypothesis cannot be rejected. Table 5 reports the selected coefficients.

Thus, we can conclude the results based on the whole sample size by saying that there is no evidence of mean reversion (i.e., $d<1$) in any single case.

Table 6 Estimates of d. Original data by subsamples

Type of disturbances	**White noise errors**		
Series	**No terms**	**With an intercept**	**With an intercept and a time trend**
Pre-Covid	0.99 (0.93, 1.06)	**0.96 (0.90, 1.04)**	0.96 (0.90, 1.04)
Covid	1.35 (1.28, 1.46)	**1.63 (1.54, 1.73)**	1.63 (1.54, 1.73)
Post-Covid	1.31 (1.15, 1.52)	**1.59 (1.44, 1.78)**	1.59 (1.44, 1.78)
Type of disturbances	Autocorrelated errors		
Series	No terms	With an intercept	With an intercept and a time trend
Pre-Covid	0.95 (0.86, 1.04)	**0.87 (0.78, 0.97)^{MR}**	0.87 (0.77, 0.97)
Covid	1.50 (1.34, 1.72)	**1.92 (1.68, 2.28)**	1.92 (1.68, 2.27)
Post-Covid	1.29 (0.76, 1.93)	**1.76 (1.32, 2.42)**	1.76 (1.32, 2.46)

Values in bold indicate the selected specificiation in relation with the deterministic terms. The values refer to the estimates of d, and in parenthesis, their associated 95% confidence bands

Table 7 Estimated coefficients in the selected models. Original data

Type of disturbances	**White noise errors**		
Series	**No terms**	**With an intercept**	**With an intercept and a time trend**
Pre-Covid	0.96 (0.90, 1.04)	1002.23 (19.15)	---
Covid	1.63 (1.54, 1.73)	917.72 (21.18)	---
Post-Covid	1.59 (1.44, 1.78)	986.61 (24.69)	---
Type of disturbances	Autocorrelated errors		
Series	No terms	With an intercept	With an intercept and a time trend
Pre-Covid	0.87 (0.78, 0.97)^{MR}	1009.85 (20.10)	---
Covid	1.92 (1.68, 2.28)	918.61 (24.69)	---
Post-Covid	1.76 (1.32, 2.42)	987.52 (12.72)	---

Column 2 indicates the estimate of d and in parenthesis the 95% confidence band for the values of d; column 3 reports the intercept and its associated t-value (in parenthesis); --- indicates lack of statistical significancy. MR indicates mean reversion

Next we separate the data in three subsamples,

Subsample 1: [16 October 2009—10 March 2023].

Subsample 2: [10 March 2020—5 May 2023].

Subsample 3: [6 May 2023—18 October 2024].

Results based on subsamples

The results are reported across Tables 6 – 9. Tables 6 and 7 refer to the original data while Tables 8 and 9 to the log-transformed data.

The results are consistent across tables. They indicate first that there is a very significant increase in the value of d during the Covid period with a slight reduction in the post-Covid era. Thus, in the pre-Covid subsamples, we find statistical evidence of mean reversion in the cases of autocorrelated errors with the original data, and in both (uncorrelated and correlated errors) with the logged values. However, for the sample referring to the Covid period, the values of d are substantially larger, ranging between 1.50 (white

Table 8 Estimates of d. Logged data by subsamples

Type of disturbances	**White noise errors**		
Series	**No terms**	**With an intercept**	**With an intercept and a time trend**
Pre-Covid	0.99 (0.93, 1.06)	**0.89 (0.82, 0.97)**^{MR}	0.89 (0.82, 0.97)
Covid	0.98 (0.88, 1.11)	**1.50 (1.43, 1.61)**	1.50 (1.42, 1.61)
Post-Covid	0.93 (0.78, 1.15)	**1.54 (1.37, 1.75)**	1.54 (1.37, 1.76)
Type of disturbances	Autocorrelated errors		
Series	No terms	With an intercept	With an intercept and a time trend
Pre-Covid	0.98 (0.90, 1.09)	**0.78 (0.70, 0.88)**^{MR}	0.77 (0.69, 0.88)
Covid	0.96 (0.80, 1.17)	**1.71 (1.53, 2.00)**	1.72 (1.54, 1.99)
Post-Covid	0.80 (0.46, 1.21)	**1.48 (1.10, 2.10)**	1.48 (1.10, 2.11)

Values in bold indicate the selected specificiation in relation with the deterministic terms. The values refer to the estimates of d, and in parenthesis, their associated 95% confidence bands

Table 9 Estimated coefficients in the selected models. Logged data

Type of disturbances	**White noise errors**		
Series	**No terms**	**With an intercept**	**With an intercept and a time trend**
Pre-Covid	0.89 (0.82, 0.97)^{MR}	6.914 (108.75)	---
Covid	1.50 (1.43, 1.61)	6.821 (297.79)	---
Post-Covid	1.54 (1.37, 1.75)	6.821 (297.79)	---
Type of disturbances	Autocorrelated errors		
Series	No terms	With an intercept	With an intercept and a time trend
Pre-Covid	0.78 (0.70, 0.88)^{MR}	6.927 (115.58)	---
Covid	1.71 (1.53, 2.00)	6.822 (331.02)	---
Post-Covid	1.48 (1.10, 2.10)	6.893 (145.24)	---

Column 2 indicates the estimate of d and in parenthesis the 95% confidence band for the values of d; column 3 reports the intercept and its associated t-value (in parenthesis); --- indicates lack of statistical significancy. MR indicates mean reversion

noise, logged values) and 1.92 (autocorrelated errors with original data). For the post-Covid, the differencing parameter ranges between 1.48 and 1.76.

These results are consistent with the prevailing view in the transport industry that any deviation in freight rates would gradually decline over time without the need to implement hard measures, at least until the COVID-19 pandemic. However, from that point onward, our findings challenge this assumption and suggest that, in response to a shock, the implementation of long-term measures becomes necessary.

As a following up step, we further investigate the pre-Covid19 period and the number of events that took place at that period and that they have been reported in Sect. "Data and methodology". Based on such events, we have considered the following sub-samples for a deeper analysis of the pre-Covid period. They are summarized in Table 10.

Table 11 displays the estimated coefficients for the original data at each subsample. It is observed that the time trend is only required in subsample 4, and the time trend coefficient is significantly negative. Looking at the estimates of d, we observe that they are

Table 10 Sub-periods examined during the Pre-Covid period

Sub-sample number	Time period examined
Sub-sample 1	16 October 2009—31 December 2010
Sub-sample 2	7 January 2011—30 December 2012
Sub-sample 3	6 January 2012—25 May 2012
Sub-sample 4	1 June 2012—26 December 2014
Sub-sample 5	2 January 2015—27 May 2016
Sub-sample 6	3 June 2016—28 September 2018
Sub-sample 7	12 October 2018—10 May 2019
Sub-sample 8	17 May 2019—6 March 2020

Table 11 Estimated coefficients on the sub-periods before Covid-19. Original values

Series	d (95% conf. band)	Intercept (tv)	Time trend (tv)
Sub-sample 1	1.72 (1.51, 2.00)	494.69 (52.39)	---
Sub-sample 2	1.51 (1.06, 2.29)	1133.31 (76.80)	---
Sub-sample 3	1.09 (0.85, 1.47)	972.60 (19.00)	---
Sub-sample 4	0.79 (0.64, 0.99)^{MR}	1380.12 (25.80)	---
Sub-sample 5	0.70 (0.53, 0.94)^{MR}	1044.65 (14.19)	−7.729 (−2.23)
Sub-sample 6	0.89 (0.74, 1.09)	591.56 (12.95)	---
Sub-sample 7	1.25 (0.89, 1.69)	899.04 (31.66)	---
Sub-sample 8	1.07 (0.80, 1.47)	724.35 (21.81)	---

Column 2 indicates the estimate of d and in parenthesis the 95% confidence band for the values of d; column 3 reports the intercept and its associated t-value (in parenthesis); --- indicates lack of statistical significancy. MR indicates mean reversion

Table 12 Estimated coefficients on the sub-periods before Covid-19. Logged values

Series	d (95% conf. band)	Intercept (tv)	Time trend (tv)
Sub-sample 1	1.70 (1.49, 1.99)	6.902 (443.50)	---
Sub-sample 2	1.53 (1.02, 2.39)	7.003 (450.45)	---
Sub-sample 3	1.04 (0.60, 1.46)	6.864 (150.24)	0.018 (1.66)
Sub-sample 4	0.78 (0.62, 0.99)^{MR}	7.225 (145.88)	
Sub-sample 5	0.66 (0.47, 0.94)^{MR}	6.945 (65.18)	−0.010 (−2.49)
Sub-sample 6	0.86 (0.71, 1.08)	6.383 (105.04)	---
Sub-sample 7	1.21 (0.86, 1.66)	6.8´2 (200.27)	---
Sub-sample 8	1.04 (0.76, 1.43)	6.586 (164.55)	---

Column 2 indicates the estimate of d and in parenthesis the 95% confidence band for the values of d; column 3 reports the intercept and its associated t-value (in parenthesis); --- indicates lack of statistical significancy. MR indicates mean reversion

much larger that for the whole pre-Covid sample; thus, the unit root null is rejected in favour of d > 1 in the first two subsamples; the I(1) hypothesis cannot be rejected in subsample 3; however, for subsamples 4 and 5, the estimates of d are respectively 0.79 and 0.69 and mean reversion cannot be rejected in any of the two subsamples, after that the estimated value of d increase and the unit root cannot be rejected in any of the remaining subsamples.

Table 12 refers to the values in logged form. We observe that they are almost identical to those based on the original data, the only difference being a significantly negative time trend in subsample 3.

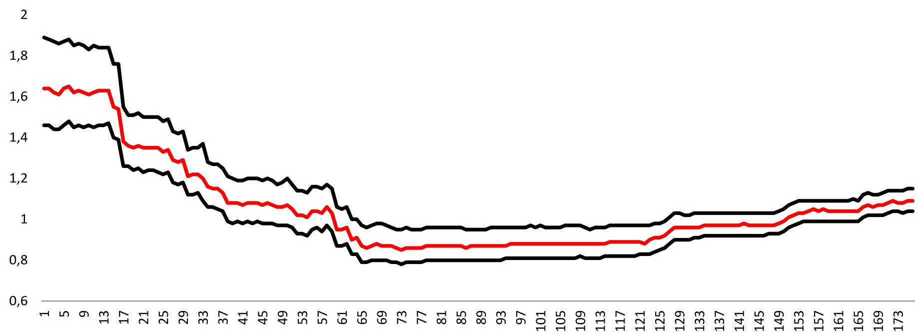

Fig. 5 Recursive estimates of d using the original data. *Note* In red, the estimates of d; in black, the 95% confidence interval

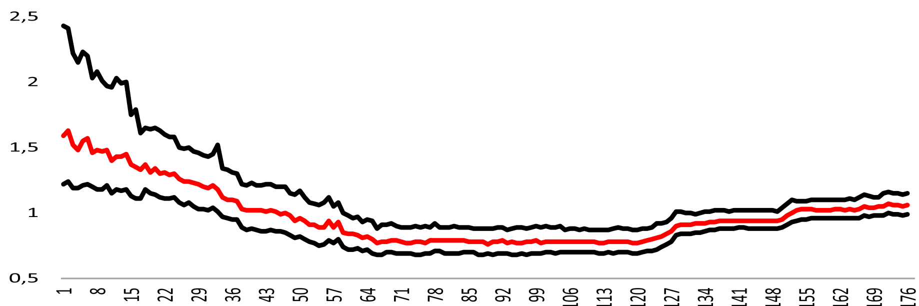

Fig. 6 Recursive estimates of d using the logged values. *Note* In red, the estimates of d; in black, the 95% confidence interval

Finally, recursive estimates of d were also performed on the sample, starting with a sub-sample with the first 52 (week) observations, and then, adding successively 4 (approximately one month) until complete the whole sample. Results are reported across Figs. 5 and 6 for the original and for the logged values.

The two figures display a similar picture, with a large value of d, much higher than 1 for the subsample containing the first 52 weeks (and thus ending at October 2010), and then start decreasing sharply until the sample containing 308 weeks (September 1015); then it comes a very of stabilization until the sample with 532 weeks (around February 2020); after that period, the time of Covid-19 pandemia, the estimates of d start increasing again.

Conclusions

In this paper we have examined the daily structure of the Shanghai Containerized Freight Index using data from October 2009 to October 2024 using fractional integration methods. The results indicate that when looking at the whole sample size the series (original and log values) are very persistent, with orders of integration above 1, and rejecting the I(1) hypothesis in most of the cases in favour of explosive roots. Thus, it seems that there is no evidence of mean reversion in any single case. However, separating the data before, during, and after the Covid-19, the results show some differences. Thus, evidence of mean reversion and thus transitory shocks are obtained if only data before Covid are used. During the pandemic there is a strong increase in the degree of integration that starts reducing after Covid.

These results are highly relevant, as they enable policymakers to implement more appropriate measures in response to economic shocks. The evidence of increased persistence observed in the SCFI following the COVID-19 pandemic suggests that shocks have become permanent in nature. While short-term interventions such as blank sailings and the idling of vessels had been sufficient prior to the pandemic, the new behaviour requires long-term and structural policy responses.

Gradually increasing the capacity of air, rail, road, pipeline, and multimodal transport could help reduce strategic dependence on maritime transport. Specifically, since rail networks are already well-established in China, Europe, and North America, a combination of rail and multimodal transport offers the most practical and scalable solution. In maritime transport, investing in alternative trade routes and expanding port infrastructure in different regions is crucial to reducing reliance on critical chokepoints. Additionally, adopting flexible fleet management regulations that allow carriers to adjust capacity based on demand forecasts, along with enhancing international cooperation to share information and coordinate shipping schedules, would help mitigate the impact of disruptions.

Finally, it is important to acknowledge that this research has certain limitations, as it focuses exclusively on the SCFI, which may restrict the generalizability of the findings to broader trends in the global maritime market. Future research should consider analyzing and comparing other major container freight indices to provide a more comprehensive view of global freight rate dynamics. Because the SCFI series begins in October 2009, the present analysis does not cover the 2008–09 Lehman-shock collapse; future work should examine whether similar persistence patterns hold for earlier periods using alternative indices such as the CCFI.

Conducting fractional integration analysis on multimodal freight data could also offer valuable insights by comparing the behavior of alternative transport costs, particularly during periods of disruption. Moreover, the potential cointegration between the Shanghai Containerized Freight Index (SCFI) and macroeconomic indicators such as GDP, both globally and for China, deserves further investigation. This may be done, for example, by using the fractional CVAR (FCVAR) approach developed in Johansen and Nielsen (2010, 2012). Although the mismatch in data frequencies (monthly for freight rates and quarterly for GDP) presents a methodological challenge, freight indices can serve as useful high-frequency indicators for economic activity. Finally, studying the interconnections between freight rates at different ports or regional indices could shed light on the spatial dynamics of container shipping markets and their responsiveness to global trade patterns.

Appendix

Using Bai and Perron (2003) tests for multiple breaks on the pre-Covid sample, we observe 4 structural breaks, that are displayed in the following table with their associated degrees of differentiation (Table 13):

Table 13 Estimated coefficients on the sub-periods before Covid-19. Original values

Series		d (95% conf. band)	Intercept (tv)
Sub-sample 1	16-Oct-09 /24-Feb-12	1.60 (1.45, 1.81)	994.48 (56.34)
Sub-sample 2	02-Mar-12/30-Aug-13	0.97 (0.83, 1.17)	1166.18 (24.78)
Sub-sample 3	06-Sep-13 /13-Mar-15	0.78 (0.51, 1.14)	1054.91 (18.01)
Sub-sample 4	20-Mar-15 /09-Sep-16	0.62 (0.47, 0.86)^{MR}	760.74 (12.01)
Sub-sample 5	16-Sep-16 /06-Mar-20	1.06 (0.91, 1.24)	732.27 (20.16)

Mean reversion is now only observed in the fourth subsample from March 20, 2015 to September 9, 2016.

Acknowledgements
Comments of the Editor and two anonymous reviewers are gratefully acknowledged.

Author contributions
GCQ wrote the introduction and literature review. She also participated in the interpretation of the results, validation of the results and conclusions. LAGA produced the codes, the obtention of the results, interpretation and conclusions. He supervised the whole work. AML proposed the original idea; he got the data and participated in the literature review and overall writing of the manuscript.

Funding
Prof. Luis A. Gil-Alana gratefully acknowledges financial support from the project from 'Ministerium de Economía, Industria y Competitividad' (MINEIC), `Agencia Estatal de Investigación' (AEI) Spain and `Fondo Europeo de Desarrollo Regional' (FEDER), Grant D2023-149516NB-I00 funded by MCIN/AEI/ https://doi.org/10.13039/501100011033. He also acknowledges support from an internal Project of the Universidad Francisco de Vitoria.

Availability of data and material
Data are available from the authors upon request.

Declarations

Ethics approval and consent to participate:
N/a.

Consent for publication
N/a.

Competing interests
There are no competing interests with the publication of the present manuscript.

Received: 2 May 2025 Revised: 29 July 2025 Accepted: 7 August 2025
Published online: 01 September 2025

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