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VOLATILITY TRANSMISSION: AN ANALYSIS OF CONTAINER FREIGHT MARKET

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İZMİR-2023

APPROVAL PAGE

DECLARATION

I hereby declare that this doctoral thesis titled as **"Volatility Transmission: An Analysis of Container Freight Market"** has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

19/05/2023

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ABSTRACT

Doctoral Thesis

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Volatility Transmission: An Analysis of Container Freight Market

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The aim of this dissertation is to investigate the volatility transmission between container and dry bulk freight markets during COVID-19 pandemic, which is a major disruption for shipping markets. Also, determining if COVID-19 caused a financial contagion between container and dry bulk freight markets is another research objective. In addition, testing the Efficient Market Hypothesis in weak form on container and dry bulk freight markets is the last research objective of this dissertation. To answer these questions, volatility structures and the transmission mechanism between these two markets are thoroughly tested, which points out the disruptive effects of COVID-19 and flow of risk between container and dry bulk freight markets in this period.

Findings indicate that although container and dry bulk freight markets mutually transmit volatility during COVID-19, the transmission from container to dry bulk market is massively stronger. The results are in line with previous research which suggests dry bulk freight rates will follow container freight rates in the upwards trending economic situation, which shipping experienced during COVID-19. In addition, the weak form efficiency for both freight markets are rejected, meaning there is information asymmetry in these markets. Results also indicated that COVID-19 caused a financial contagion between dry bulk and container freight markets.

In summary, this dissertation materializes the essence of disruptive effects of COVID-19 on container and dry bulk freight markets, which poses significant systemic effects on financial markets and institutions; it also highlights the interconnectedness of these two markets.

Keywords: Volatility Transmission, Market Efficiency, Freight Markets, COVID-19.

ÖZET

Doktora Tezi

Volatilite Geçişkenliği: Konteyner Navlun Piyasası Üzerine Bir İnceleme

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Bu tezin amacı, denizcilik piyasaları için bozucu etkileri olan COVID-19 pandemisi sırasında konteyner ve kuru dökme yük piyasaları arasındaki oynaklık geçişkenliğini araştırmaktır. Ayrıca, COVID-19'un konteyner ve kuru dökme yük piyasaları arasında finansal bir bulaşmaya neden olup olmadığının belirlenmesi de araştırmanın amaçlarından biridir. Ek olarak, Etkin Piyasa Hipotezinin konteyner ve kuru dökme yük navlun piyasaları için zayıf formda test edilmesi de bu tezin araştırma amaçları arasındadır. Bu araştırma sorularını yanıtlamak için, bu iki piyasanın oynaklık yapıları ve aralarındaki oynaklık iletim mekanizması kapsamlı bir şekilde test edilerek konteyner ile kuru dökme yük navlun piyasaları arasındaki risk akışına ve COVID-19'un yıkıcı etkilerine işaret edilmiştir.

Bulgular, konteyner ve kuru dökme yük navlun piyasalarının COVID-19 sırasında birbirleri arasında karşılıklı olarak oynaklık geçişkenliğini saptamasına rağmen, konteyner piyasasından kuru dökme yük piyasasına doğru olan geçişkenliğin çok daha güçlü olduğunu göstermektedir. Sonuçlar, tıpkı COVID-19 döneminde genel navlun oranlarının olağanüstü seviyede arttığı gibi, yukarı yönlü ekonomik durumda kuru yük navlun oranlarının konteyner navlun oranlarını takip edeceğini öne süren önceki araştırmalarla uyumludur. Ayrıca, her iki navlun piyasası için de zayıf formda Etkin Piyasa Hipotezi reddedilmiş, bu piyasalarda bilgi asimetrisi olduğu sonucuna varılmıştır. Son olarak COVID-19'un konteyner ve kuru dökme yük navlun piyasaları üzerinde finansal bulaşıcılık etkisi yarattığı tespit edilmiştir.

Özetle bu tez, konteyner ve kuru dökme yük navlun piyasalarının birbirleriyle olan bağlılıklarını vurgulayarak; COVID-19'un bu piyasaların oynaklığı üzerindeki yıkıcı etkilerinin özünü yakalamanın finansal piyasalar ve kurumlar açısından önemli sistemik etkilere sahip olabileceğini göstermektedir.

Anahtar Kelimeler: Volatilite Geçişkenliği, Piyasa Etkinliği, Navlun Piyasaları, COVID-19.

VOLATILITY TRANSMISSION: AN ANALYSIS OF CONTAINER FREIGHT MARKET

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ABBREVIATIONS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
APM	Arnold Peter Moller
ARCH	Autoregressive Conditional Heteroskedasticity
BDI	Baltic Dry Index
BEKK	Baba Engle Kraft Kroner
CMA-CGM	Compagnie Maritime d'Affrètement Compagnie Générale Maritime
COSCO	China Ocean Shipping Company
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EMH	Efficient Market Hypothesis
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
HMM	Hyundai Merchant Marine
IFO	Intermediate Fuel Oil
KPSS	Kwiatkowski Phillips Schmidt Shin
LM	LaGrange Multiplier
MLM	Multivariate LaGrange Multiplier
MSC	Mediterranean Shipping Company
ONE	Ocean Network Express
OOCL	Orient Overseas Container Line
RBDI	Return of Baltic Dry Index
RSCFI	Return of Shanghai Containerized Freight Index
SCFI	Shanghai Containerized Freight Index
SIC	Schwarz Information Criterion
TEU	Twenty-foot Equivalent Unit
UNCTAD	United Nations Conference on Trade and Development
USD	United States Dollars
VAR	Vector Autoregression

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INTRODUCTION

This thesis examines the COVID-19 pandemic's volatility transmission between the dry bulk and container freight sectors. The overall structure of the dissertation is offered in the introductory section by outlining the background of the research, the objectives of the study, and the thesis' structure.

Research Background

Shipping is highly volatile, cyclical and capital-intensive industry defined by extreme highs and lows, which makes market volatility information material and relevant for economic decisions as diversifying portfolio, forecasting, and hedging in maritime industry. The fundamental cause of this is the inelastic nature of the supply curve in the shipping markets over the short term. If a ship is ordered in accordance with the future expectations deriving from the current market conditions, it may enter the market in roughly three years and to increase the supply of carrying capacity. Therefore, the conditions when the ship enters the market is unknown, or highly ambiguous at best, when the building order is placed. Demand for shipping services is tough to estimate, despite the fact that incoming and impending removal of capacity can easily be monitored through shipyards. This situation is one of the main contributors to the cyclicality of shipping markets. Knowledge about dissemination of volatility in shipping can assist shipping companies in improving their operational efficiency by making them more responsive to market changes. When a shipping company can accurately foresee market changes, it can respond swiftly and adjust its operations accordingly. Also, volatility transmission in shipping industry is crucial for policymakers seeking to improve the economic outlook of individuals and organizations dependent on shipping industry. By keeping the flow of volatility between shipping markets in mind, they can promote pro-industry economic policies more accurately, since they would more accurately estimate the effects of introducing new shocks to a freight market on the other one. Therefore, understanding the volatility transmission between container and dry bulk freight markets could provide an

effective risk management mechanism, which could contribute to the decision making process in shipping.

As Stopford (2009) indicates, dry bulk freight market is considered a primary indicator for international trade and demand for raw materials whereas the price levels in container freight market is a direct reflection of international trade and demand for semi-finished and finished products. Due to these direct links of freight rates with the world economy, freight rates are considered as leading indicators for global economic climate (Açık and Başer, 2021). Thus, it is evident that freight rates are situated at the inner circle of global money stream (Alizadeh and Muradoğlu, 2014). Therefore, it is crucial for decision makers in the maritime industry and financial markets to grasp the dynamics volatility transmissions between container and dry bulk freight markets.

The Efficient Market Hypothesis (EMH) represents the foundation of the modern financial theories from derivatives valuation to capital assets pricing. It tackles the concept of available information from various aspects. For many years, EMH being a major research area in the specialized literature academics and economics have studied the concept of efficiency an applied it to a plethora of markets. And shipping, which is an integral industry for global economy, is also been studied in the literature of maritime economics in the light of market efficiency (Evans 1994; Kavussanos and Alizadeh 2002; Hale and Vanags 1989; Veenstra 1999; Adland and Cullinane 2005; Adland and Strandenes 2006). Their findings suggest that various segments of shipping market are indeed inefficient. Meaning in shipping markets, participants can easily out-play and out-profit each other due the to information asymmetry in the market.

Research Questions and Aim of the Study

This dissertation is constructed upon three research questions; (i) Is there a transmission of volatility and risk between container and dry bulk freight markets during COVID-19 and what is its direction? (ii) Did COVID-19 cause a financial contagion between container and dry bulk freight markets? (iii) Where do these markets stand in terms of EMH?

These questions gain importance considering it is crucial for decision-makers in the maritime industry, financial markets, and businesses that rely on shipping to get their products to market and their materials from suppliers to understand volatility transmissions between the container and dry bulk freight markets. This makes information regarding volatility in this market material and relevant for decisions related to portfolio diversification, forecasting, and hedging in the maritime industry. Also, this study aims to be a forerunner by methodologically explaining the effects of COVID-19 on freight markets in the light of financial contagion.

Organization of The Dissertation

Chapter one examines the defining characteristics of container freight market while providing a market outlook for its current situation.

Chapter two examines the concept of volatility transmission, financial contagion, and efficient market hypothesis with detailed literature review. Also shipping market volatility literature is discussed and prevailing hypotheses of lead-lag relationship between container and dry bulk markets are laid out in this chapter.

Chapter three examines the methodology of the study, and introduces the data set used for analysis.

Chapter four includes data preparation process and the pre-tests imposed by the financial time series analysis. In addition, the results of the conducted pre-tests, model selection process, findings of the estimation, and post estimation diagnostics are also in this chapter.

Lastly, the study's findings are assessed, academic and practical ramifications are offered, and study limitations and suggestions for future research are presented as a conclusion.

CHAPTER ONE
CONTAINER SHIPPING FREIGHT MARKET

This chapter will explore the mechanism behind container shipping freight market and its defining characteristics. As a first step to understanding the main aspects of the container freight market, which is the main component of liner shipping market alongside Ro-Ro and passenger transport, finding out if the market is competitive is crucial. Also understanding the cyclical nature of the container freight market is material for drawing conclusions on the industry's long-term profitability.

1.1. CHARACTERISTICS OF CONTAINER FREIGHT MARKET

Throughout the relatively brief history of containerization, the shipping of containerized goods by sea has greatly expanded trading between countries with differing relative economic advantages (Stopford, 2009). Since early 2000s, there were dramatic increase in the efficiency of container shipping and port operation, thanks to the rise of specialization and technical advancement, making container transportation essential to the global economy (Luo et. al 2009). Despite its exponential growth and indispensable position for the global economy, it is material to grasp characteristics of container freight market to derive conclusions regarding its working mechanisms, as Duru (2019) argued the rest of the shipping markets tend to follow freight markets lead. Almost usually, other markets react swiftly to any significant shifts in the freight industry. Throughout the extensive literature, several defining characteristics of container freight market are emphasized.

1.1.1. Volatility

It is important to keep in mind that costs which generate the freight rate as a result are highly volatile and can swing drastically in a short periods (Stopford, 2009). As a result, shipping lines' profits swing constantly, and cargo owners cannot reliably estimate shipping expenses. This unpredictability is a well-known feature of freight markets and shipping in general. From the year 2000, shipping lines and cargo owners

have found themselves in situations of both extremely high and relatively lower freight rates, and this volatility has not subsided with time. These volatility of profitability for shipping lines and transportation costs for shippers are not a recent occurrence, but rather a defining feature of the container freight market. To visually examine the volatile structure of the market historical data of Shanghai Containerized Freight Index (SCFI) are given in Figure 1.

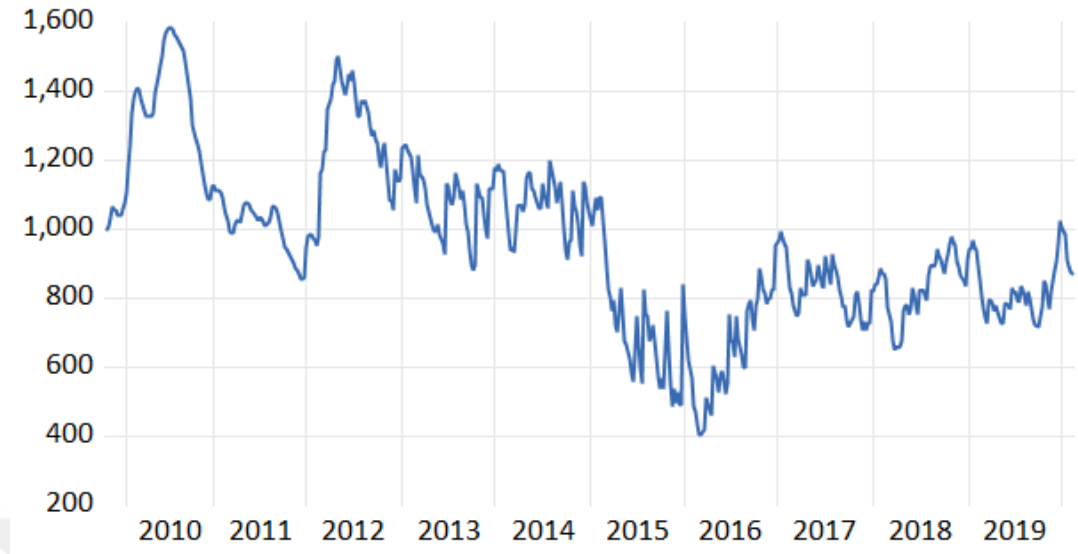
Figure 1: Historical Data of SCFI



Source: Bloomberg, 2022.

Upon first glance at Figure 1, it is impossible to miss how after the start of 2020, which coincides to the period where COVID-19 started spreading globally, freight rates started to increase exponentially. Due to the fact that market explosion dwarfs all the past trends in container freight market, the volatility of the period before COVID-19 should be looked at separately for visual clarification purposes.

Figure 2: Historical Data of SCFI Before COVID-19



Source: Bloomberg, 2022.

When Figure 2 is inspected, sharp swings in container freight rates are first to be noticed since the SCFI started being published in late 2009. This volatile situation makes the market unpredictable, making it even more riskier to invest in. Memişoğlu (2018) employed an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model to examine the volatility of container freight markets. Their findings show a negative leverage effect, high shock persistence, volatility clustering, and extremely high shock sensitivity for the volatility properties of container freight market. A more in-depth explanation of container freight market volatility will be explored in Chapter 2 and Chapter 3.

Volatility clustering, which implies mild fluctuations in the market were followed by mild fluctuations, where wilder fluctuations of the market are followed by even wilder fluctuations are one of the main factors contributing to business cycles. That brings us to the next defining characteristics of container freight market: cyclicality.

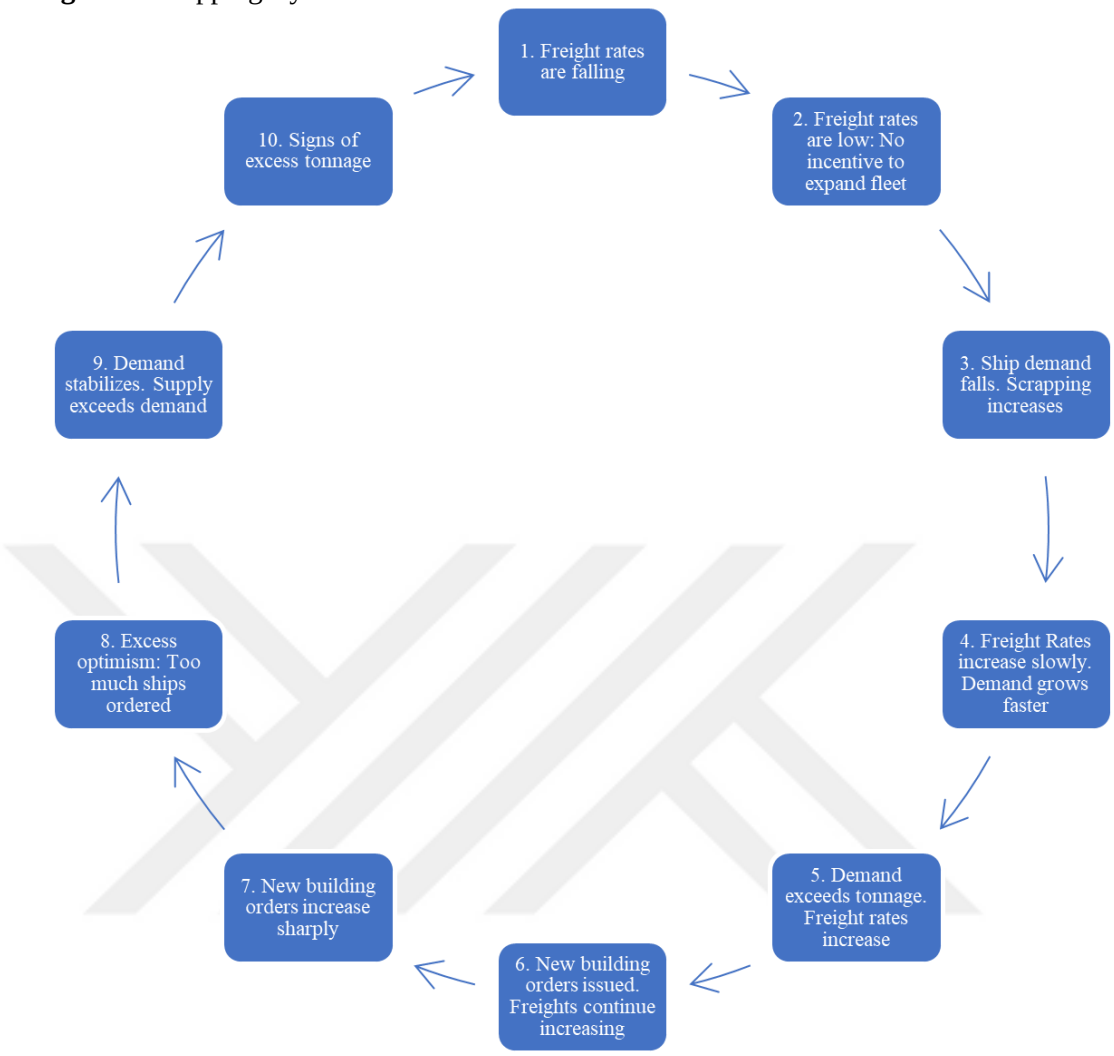
1.1.2. Cyclicality

Cycles of vessel overstock and capacity shortages are commonplace in the container shipping business. Due to shipping being a derived demand, a drop or

contraction in global aggregate demand leads to a corresponding drop for transportation services demand, which in turn will cause shipping companies to construct fewer ships and scrap some that are not in use, contributing to the cyclical nature of both maritime industry and global economy (Stopford, 2009). Shipowners place large orders for new vessels while demand is rising, leading to periods of overcapacity that last far beyond the norm. Easy access to ship financing, historically low interest rates, and extreme confidence in future demand have all contributed to increased fleet investments in recent years (Randers and Göluke, 2007).

When the economy is in a bind, production, consumption, and the need for transportation all go down. During this phase, which can be thought of as the start of the shipping cycle, where freight rates, company revenues, and market profitability all decrease (step 1), and there are consequently no incentives to increase the fleet's tonnage (step 2). This leads to a decrease in shipping demand and the eventual scrapping or mothballing of more vessels. Transportation costs have stayed relatively low (step 3). The initial three stages of the maritime cycle represent its initial phase. Due to inelastic demand, when the economy begins to improve (step 4), the fleet expands very slowly while demand expands very quickly. The higher part of the cycle occurs between steps 5 and 10: demand exceeds supply, shortages in tonnage are evident, freight rates increase as demand keeps outstripping supply, and shipbuilding orders surge. The problem with too much optimism is that it can lead to an overload of orders. A typical snapshot of a shipping cycle development just discussed above is given at Figure 3.

Figure 3: Shipping Cycle Mechanism



Source: Adapted from Sanchez (2017).

It usually takes a long time to break the cycle that keeps overcapacity situations going. Notteboom (2012) argues absorbing excess capacity is challenging for many intertwined factors. To begin, shipyards are reluctant to comply with shipowners' requests to cancel orders or postpone deliveries. Second, because of the surplus on the market, prices on the second hand market are considerably cheaper, charter rates are lower, and vessel construction costs are lower. Finally, scrap values are lower in a depressed market, so shipowners have little incentive to cut capacity through scrapping vessels. Hence, the downward spiral is actively reinforced by the maritime industry's four main subsectors: the freight market, second hand market, shipbuilding market, and the scrap market (Duru, 2019). Because of the reasons explained above and herd

behavior according to Lee and Yip (2018) strong demand for container shipping services during periods of high freight rates, shipping companies have been rushing to place orders for larger and more efficient container vessels. While a decrease in the price of sea transport can stimulate demand in the short term, it will inevitably lead to serious issues in the long run. Historical cycles in shipping since World War 1 are given in Table 1.

Table 1: Shipping Cycles

No	Period	Duration	Major Event
1	1911-1913	3	World War 1
2	1921-1925	5	-
3	1926-1937	12	Worldwide Depression
4	1939-1946	8	World War 2
5	1945-1951	7	Korean War
6	1952-1955	4	Vietnam War & Suez Canal Closure
7	1957-1969	13	Six Days War & Oil Crisis
8	1970-1972	3	-
9	1973-1978	6	Suez Canal Reopening
10	1979-1987	9	Iranian Revolution
11	1988-2002	15	Asian Economic Crisis
12	2003-2007	5	China Boom
13	2008-2013	6	Sub-prime housing crisis
14	2020-2022	2	COVID-19

Source: Stopford, 2009; Goulielmos, 2020.

Reinhart and Rogoff (2008) argues that if a market is cyclical by nature it is folly to anticipate major changes related to its cyclicality. Especially the financial markets, regularly ride these cycles so to speak. The motivations and behavioral biases in human nature still remain, no matter how many political, economic, legal or technological developments occur in a market over the years.

1.1.3. Capital Intensity

The container shipping sector is very capital-intensive due to the mix of owned and leased assets and the vast range of pricing structures (Brooks 2000). Since their businesses are essentially asset driven, container shipping companies rely heavily on effective asset management. Equipment management, increasing the usable deployment life cycle and asset value of ships, increasing machinery safety and decreasing potential liabilities, and improving capacity management are all examples of common asset management decisions made by shipping companies (Notteboom, 2012). In the short term, vessel capacity is very inflexible due to fixed schedules, seasonality impacts, and cargo imbalances on between economic regions, all of which contribute to the difficulty of fleet capacity management. As services compete for customers, capacity is typically added as extra sequences to existing routes. This method has substantial fixed costs for the lines. At the heart of the industry's riskiness are the substantial capital expenditures and the unwavering regularity of liner service schedules, regardless of whether or not the loaded cargo is sufficient to fully optimize vessels capacity (Stopford, 2009). With the rise in vessel orders, building capacity tightened, driving up newbuilding prices as owners raced for a piece of the earnings bubble. According to the market report of VesselsValue (2022) the price tag for an order of 4,250 Twenty-foot Equivalent Unit (TEU) Panamax container vessel in September 2020 was $23.6 million United States Dollars (USD). This same order would have set the company back $65.5 million by September 2021, an increase of a shocking 177.7 percent.

Beginning in 2010, larger liner shipping companies started placing more orders for new vessels, ordering even larger vessels, and consolidating their alliances simultaneously (Sanchez and Wilmsmeier, 2011). This situation increased already high barriers of entry to the container shipping market to whole new levels with these large over 20,000 TEU capacity ships costing $125 million (VesselsValue, 2022). In turn, this seemingly impassable barrier generated even more consolidation in the market, which brings us to the next defining characteristic: the oligopolistic composition of the market.

1.1.4. Oligopolistic Market Composition

Liner shipping market is known to be traditionally oligopolistic throughout the years. The liner shipping market were basically revolving around entities known as liner conferences. Rates, trips, and other matters of mutual interest were arranged at these conferences, which may merely be casual get-togethers or sporadic, irregular meetings. This may simply be an unwritten agreement between lines' traffic representatives to check in with each other before making any rate changes. However, conferences are typically organized in a formal manner, complete with officers, committees, routine and ad-hoc meetings, rules, and sanctions (McGee, 1960). Therefore, freight rate setting, supply regulation, and the allocation of markets amongst each other were the primary focus areas for any given liner conference. Jansson and Shneerson (1987) describes this situation as liner shipping market being almost completely cartelized by these conferences due to their practices such as shipper discrimination, loyalty rebates, membership restrictions, cargo quoting, sailing quoting, and quantity pooling. Most of the freight carried by the members of the conference has rates that have been collectively set by the conference and published in tariffs. Freight rate adjustments for conferences usually occurred every six to twelve months. In addition, these adjustments to freight rates at various conferences increased and decreased in tandem (McLachlan, 1963).

After late 2008, with their immunity from anti-monopoly laws and regulations is revoked, the liner conferences were outlawed globally (Sys, 2009). This situation first brought the mergers and acquisitions trend amongst the container shipping companies, which resulted in the market having fewer carriers than 1995, contributing to market concentration (Fusilo, 2009). Therefore, freight rates for shippers rose due to the concentration and lack of competition in the liner shipping. Ducruet et al. (2010) claimed that line service networks aimed to achieve the optimal balance between cost and service quality through the use of economies of scale via employing larger and larger vessels, which led to even more global traffic concentration. This strategy led to fewer ports of call per route. Ports of developing countries had access to only a third of the world's container shipping companies, which were only 28 in the whole world at that time, meaning that businesses at those countries had fewer options and less

competition, both of which are empirically linked to higher freight rates (Goulielmos, 2017).

In addition to the waves of mergers and acquisitions, the now outlawed conferences rapidly replaced by global shipping alliances. When multiple ocean carriers come together to form a cooperative agreement, they are said to have formed a shipping alliance. Through international cooperation, the members of this agreement cover a wide range of trade corridors. These consortia of shippers agree to pool their resources by sharing vessels so that they can serve a wider portion of the shipping industry. To a large extent, carriers pool their cargo ships into larger fleets within each alliance. This allows them to use ships operated by other companies. It is common practice for shipping companies to swap containers for one another. Since then numerous alliances in the industry were formed and disbanded however. Container shipping industry is currently dominated by three major alliances which encompasses 82.2% of the global TEU capacity can be seen in Table 2.

Table 2: Major Container Shipping Alliances as of 2023

Alliance	Member Lines	Details
2M	Maersk, MSC	Formed in 2015, will be disbanded in 2025, controls 8.9 million TEUs capacity
Ocean	CMA-CGM, COSCO, OOCL, Evergreen	Formed in 2017, controls 7.9 million TEUs capacity
THE	Hapag-Lloyd, ONE, Yang Ming, HMM	Formed in 2017, controls 4.8 million TEUs capacity

Note: MSC=Mediterranean Shipping Company, CMA-CGM=Compagnie Maritime d'Affrètement Compagnie Générale Maritime, COSCO=China Ocean Shipping Company, OOCL=Orient Overseas Container Line, ONE=Ocean Network Express, HMM=Hyundai Merchant Marine

Source: Developed based on Alphaliner (2023).

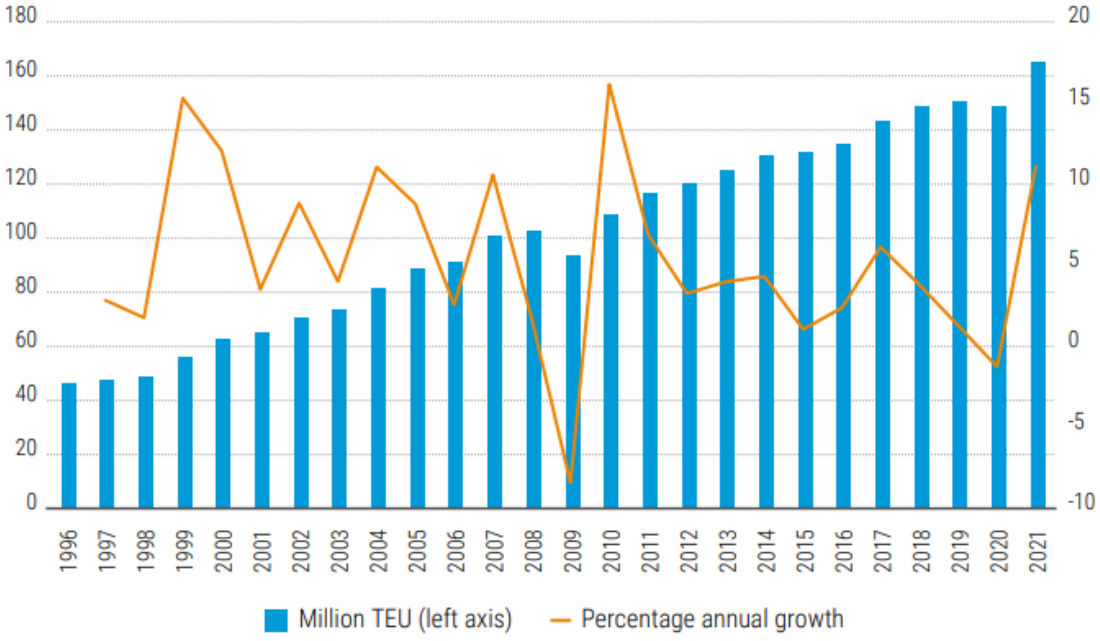
According to Stopford (2009), the operational costs of a shipping company account for over 67% of the total cost of operation. Most of this sum is attributable to variable expenses such as bunker costs, which are 46%, and port fees, which equate to 21%. The best way for shipping companies to cut these costs is to pool resources like vessels, ports, and communication networks along specific routes. This is a major motivator for the development of shipping alliances and other forms of vessel sharing arrangements. One of the most significant benefits of being a part of an ocean alliance

is the financial boost it provides to individual carriers, allowing them to invest in larger vessels. Because of this, shipping companies can grow their operations and have an effect on the international economy (Sys et al. 2011).

1.2. OVERVIEW OF CONTAINER FREIGHT MARKET

With the COVID-19 pandemic driving demand for consumer goods, especially in East Asia, containerized trade flourished in 2021. In 2021, volume increased to 165 million TEU, after dropping by 1.3% in 2020 as seen in Figure 4. This was fueled by increased spending on consumer goods, particularly via e-commerce, as well as the release of pent-up demand, restocking, and continuation of spending as a result of improved global economic conditions.

Figure 4: Global Containerized Trade, Millions TEU



Source: United Nations Conference on Trade and Development (UNCTAD), 2022.

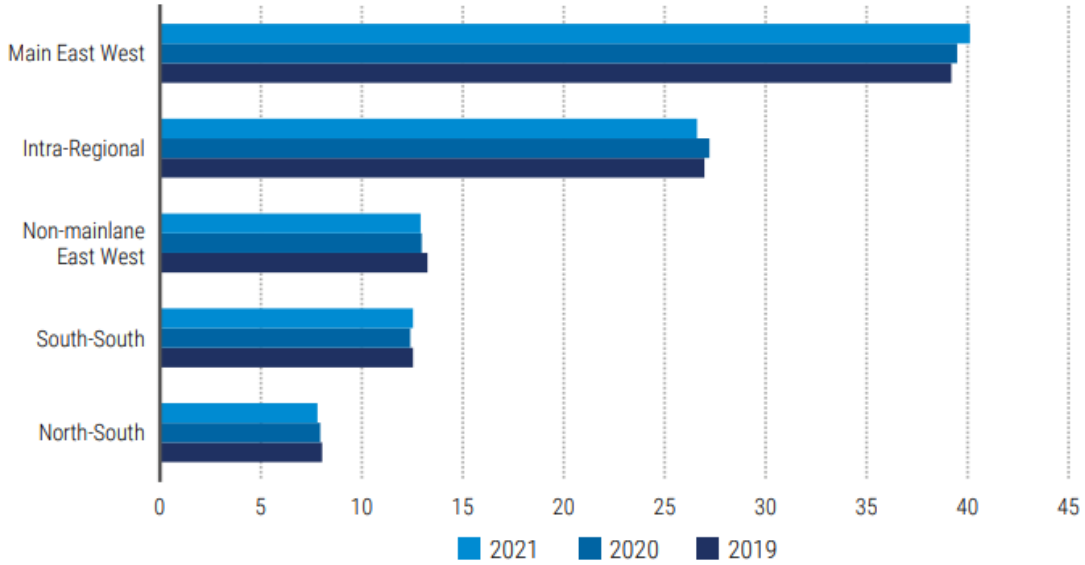
The supply and demand structure of the container freight market remained abnormal all through 2021. A resurgence of 11% in worldwide containerized trade volumes, on the other hand, added to the stresses already being felt by carriers and ports around the world. Simultaneously, freight rates rose due to COVID-19 related supply chain disruptions, including increased congestion in ports and inland issues that

lowered global supply chain capabilities. With the increasing freight rates, container lines started to increase overall capacity in the market as a result of the cycle mechanism discussed in previous section kicking in. Since ports, storage facilities, hinterland links, truck services, and trains couldn't easily keep up to sudden increase in capacity and traffic, adding more ships only made congestion worse. The number of days that containers were delayed on the trade route between the Far East - North America rose from 2 days in the first quarter of 2020 to 12.6 days in the fourth quarter of 2021 (McKinsey, 2022).

1.2.1. Traffic Distribution

In regards to the traffic distribution among the shipping routes approximately 40% of all containerized trade occurred along the major East-West routes connecting Asia, Europe, and the Americas. South Asia-Mediterranean and other auxiliary East-West routes total at 12.9%, where South-South trade routes like Sub-Saharan Africa to Latin America is at 12.5%. In addition, North-South trades such as Europe-Africa route accounted for 7.8% (UNCTAD, 2022).

Figure 5: Global Containerized Trade by Routes, in Percentages



Source: UNCTAD, 2022.

Because of China's Zero-COVID policy, congestion was severe in the country's major export centers like Shanghai, Qingdao, and Tianjin. It was also very severe in the United States close to the key West Coast commerce gateways of Los Angeles and Long Beach. For the non-hub geographies, especially in developing countries where carriers can often avoid congested ports if wait times become unacceptable to make up for the longer waiting times at major ports (Bhonsle, 2022).

1.2.2. Blank Sailings

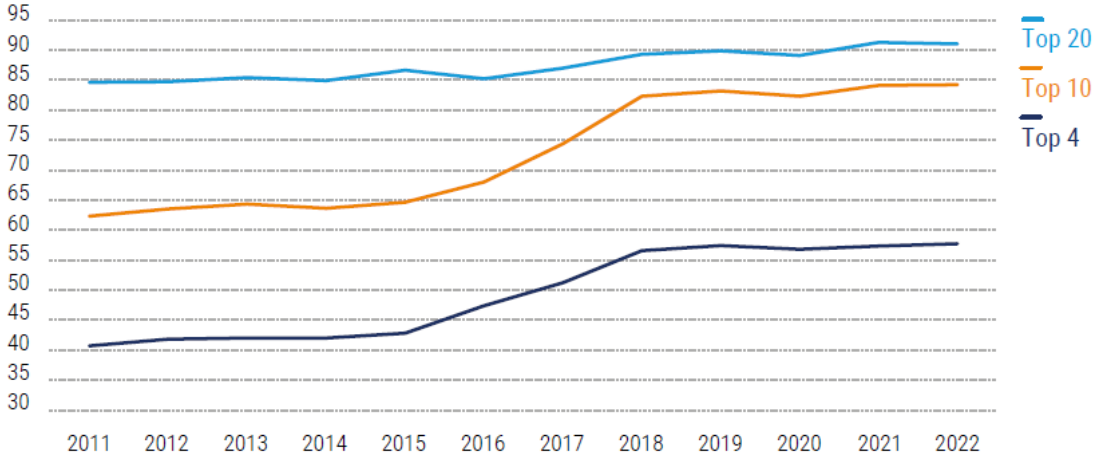
When Figure 5 is inspected, it can be seen that shipping lines tended to reduce their services to non-mainline routes, while increasing their services on major routes. The exports of many developing countries were severely impacted by these market dynamics, when freight rates reached record highs. Blank sailings and cancelled port calls are only two examples of the carriers' behavior that has shippers and governments of those countries worried. This was not because of a lack of consumer interest, but rather because shipping companies prioritized the more lucrative Asia-to-North America routes at the expense of European, Sub-Saharan African, and Oceanian ports between 2019 and 2021 (Australian Competition and Consumer Commission, 2022). These practices were put on the radar of global and regional authorities because of public outcry. The Ocean Shipping Reform Act was enacted by the United States Congress in June 2022 with the goal of encouraging a more effective, competitive, and cost-effective maritime transportation sector (Lewis, 2022). The Korea Fair Trade Commission sued scores of shipping firms, both big and small, in anti-monopoly cases in 2022 because of their high freight costs (DHL, 2022). As a result of the European Union's Consortia Block Exemption Regulation, which enables container shipping firms to share confidential business data for optimizing fleet size, sailing schedules, and vessel deployment. 10 European trade groups have called for an immediate review of the regulation. These groups represent cargo owners, freight forwarders, shippers, terminal operators, and other interested parties. The present regulation, which will be in effect until April 2024, was renewed in April 2020 (Feport, 2022). As a result of shippers' complaints in China, the shipping industry has met with regulators to discuss whether or not the fees are warranted. Lines operating in the Common Market for

Eastern and Southern Africa's shipping industry have come under scrutiny for their coordinated hike in freight prices (UNCTAD, 2022).

1.2.3. Market Structure

Remembering the market structure of the container shipping industry discussed in previous section, horizontal consolidation has occurred through frequent mergers and acquisitions in response to oversupply of capacity. By expanding into terminal operations and other services in logistics, shipping companies have also sought vertical integration. In addition, they have formed strategic alliances to further their goals. With the help of vertical integration, the four main container shipping companies are now able to provide a greater variety of terminal services directly. China COSCO Shipping and Arnold Peter Moller (APM) Terminals, respectively connected with two major Chinese and Danish shipping lines, are today the two largest container terminal operators in terms of throughput. Strategic alliances are still the most typical form of partnership in container shipping market. More than 80% of global capacity is now under the management of carrier members of such alliances (Alphaliner, 2023). To facilitate their East-West route services, the major nine container operators today form three strategic alliances in which no smaller carriers participate. Being tenants of terminals and providers of shipping services, carriers and their alliances now have a more powerful voice in negotiations with port authorities because to integration.

Figure 6: Market Shares of Top 4, Top 10, and Top 20 Carriers in Percentage

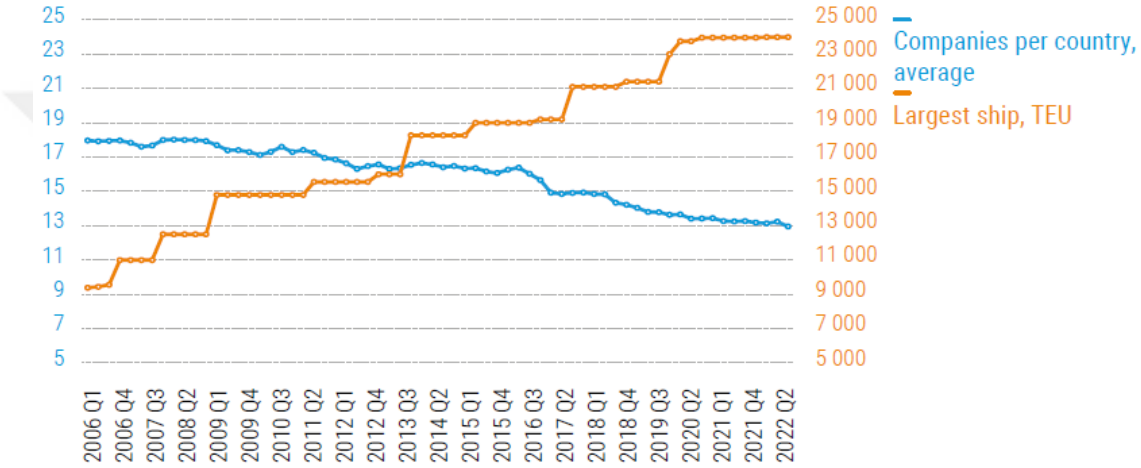


Source: UNCTAD, 2022.

The top 20 carriers therefore raised their market share of containers carried from 48% in 1996 to 91% in 2022. In addition, over the past five years the top four carriers have expanded their market shares to the point where they control more than half of the world's capacity which can be seen in Figure 6 above (UNCTAD, 2022).

The variety of service providers available in any nation is an essential factor. This has been generally declining. Figure 7 shows that this number fell from an average of 18 in 2006 to an expected 13 in 2022.

Figure 7: Average Number of Liner Services per-Country and Size of Largest Vessel



Source: UNCTAD, 2022.

Simultaneously, the average size of the largest ship visiting each country nearly tripled. The growth of ships outpaces the growth of their cargo holds, which is bad news for companies with lower volume requirements. However, the number of companies providing these services decreased in 110 nations, most notably in some small island developing States, where a duopoly of just two carriers plummeted to a monopoly of just one. This change mostly occurred between 2006 and 2010, the period during which the traditional liner conferences were being transformed into strategic shipping alliances.

CHAPTER TWO
VOLATILITY TRANSMISSION

This chapter will explore the concepts of volatility transmission and financial contagion. As a first step the term volatility transmission is discussed. Then, the concept of financial contagion and its properties are explained. After discussing the working mechanism of financial contagion, the methods to detect volatility transmission and contagion are briefly summarized. After the literature regarding volatility transmission is reviewed, the theoretical background of the dissertation is laid out. Therefore, the EMH, which is the main theory behind this dissertation, is discussed in this section.

2.1. VOLATILITY TRANSMISSION AND FINANCIAL CONTAGION

Two key measures that are used to assess the risk of financial asset investments are volatility and correlation. The volatility of financial asset returns are time varying, as Alexander (2008) argued, and this has a significant implication for risk quantification. Volatility is thus a key problem in financial economics.

Financial contagion has been a major concern for the past 20 years, particularly now that the global financial crisis and the subsequent sovereign debt crisis have re-ignited interest in the subject among academics. For investors and decision-makers, the contagion effects are crucial in selecting the best asset allocation, crafting monetary and fiscal policy, and mitigating risk. The channels of contagion may open a door to negative effects on the financial markets. Hence, the probability of a financial crisis spreading will be reduced by efficient regulation and public initiatives.

Financial contagion has a number of wide and narrow definitions, but there is not a consensus on it yet. According to the extent of its spread and the pathways via which it occurs, the description of contagion is categorized through literature research. Contagion has been characterized as a significant increase in links across various markets following a shock to one economy in relation to the spread of financial shocks between multiple countries (Seth and Sighania, 2017). The significance is the alteration in the level of market correlation before and after a financial shock. The key

issue is the increase in correlation following a financial shock. It is not necessarily contagion; it is simply reliance if two markets continue to exhibit significant levels of correlation both before and after a shock. If there is a considerable increase in cross-market linkages following a crisis, it indicates that there was contagion because the transfer mechanism was enhanced. This is the most common and accepted definition of shift contagion. The second group is called channel-dependency. Other than those, only the transmission shock is thought to be contagious and is referred to as pure contagion. Contagion is not thought to exist when it comes to the fundamentals of transmission like commerce, economic relationships, or connected capital markets. Forbes and Rigobon (2002) claim that the primary financial markets mentioned in the literature on contagion are the foreign currency market, the international stock market, and the bond market. Fundamentals-based contagion is also offered as a general definition by Calvo and Reinhart (1996). It speaks of the dissemination of financial shock via physical or financial ties. According to a more stringent definition from Forbes and Rigobon (2002), contagion happens when cross-country or cross-market correlations rise relative to correlations during "tranquil" times during "crisis times." In order to avoid selecting the incorrect time period for the research, this distinction is essential when doing an empirical analysis. A simple strategy is to pick a period of stability that is historically typical and a time of unrest following a crisis. The co-movement across markets may be substantial during periods of stability, but the authors contend that for a condition to be considered contagion, co-movements must dramatically increase following a shock to one market. They refer to the condition as interdependence rather than contagion if the level of co-movement was already strong prior to the shock and remains strong after it.

According to the logic of a contagion test based on correlation, market contagion during a crisis is indicated by a noticeably higher correlation between these markets. In other words, if the price of one market drops, so does the price of the other. According to Edwards (2000), contagion occurs when the scope and intensity of shocks' global dissemination exceeds what market players anticipated. In a nutshell, The transmission of shocks from one market to another was described as contagion by Samarakoon (2011). It is emphasized how crucial it is to distinguish between the consequences of shocks occurring in stable times and those during times of crisis.

A worldwide shock is not required for the second reason of contagion, which is connected to investor behavior, to occur. This kind of investing conduct can be characterized as irrational. Financial panics, herding tendencies, a decline in confidence, and increased risk aversion are a few examples of irrational factors that can induce contagion.

The relevance of building multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for understanding the co-movements of financial returns was stressed by Silvennoinnen and Terasvirta (2009). Multivariate GARCH models have also been applied to studies of contagion to look at the consequences of transmission. There are two methods for determining contagion. One of them is causality testing, while the other is dynamic conditional correlations based on multivariate GARCH models. The empirical research demonstrates that there is market contagion if cross correlations between markets rise during a crisis period. Moreover, the direction of the contagion is not reported by the correlation between two markets. As a result, the Granger causality approach is more suited for measuring spillovers. These two strategies are thought to complement one another when used simultaneously.

With information flows, the idea of volatility transmission gains significance (Chan et al, 1991). In this regard, an intriguing question is raised regarding the possibility of information or market volatility spreading to other markets. Transmission mechanisms are becoming more and more crucial for market efficiency, risk management, portfolio diversification, and asset pricing (Güloğlu et al. 2016).

Since Baillie and Bollerslev's initial research in 1991 and Lin et al.'s original studies in 1994, a substantial body of evidence has accumulated addressing the behavior and causes of financial asset return volatilities. They demonstrate how volatility varies across different assets, classes of assets, time frames, and nation. At that time, this information has been put to use in a number of financial contexts, including asset pricing, portfolio construction, and market risk management. In the literature, the seemingly unrelated cross-market volatility interdependence is frequently referred to as having volatility transmission effects (Leung et al, 2017). When investors utilize foreign currencies to purchase equity on global financial

markets, exchange rate volatility can have an impact on the volatility of equity markets (Kanas, 2000).

Also, the frequency of financial crises has increased recently, generating a great deal of interest in how crises affect the transmission of volatility. The word "contagion" is used by Bekaert et al. (2005) and Bekaert et al. (2014) to describe the intensification of market co-movements and volatility transmission during crisis situations as compared to non-crisis periods.

Contagion is categorized in the financial literature as either fundamental contagion or pure contagion. The phrase "fundamental contagion" is used by Dornbusch et al. (2000) to support their argument that economic fundamentals might explain contagion. The foundational study of Lin et al. (1994), which attributes contagion as a by product of irrational investor behavior that might result in illogical occurrences such as herd mentality and financial panicking, makes reference to the idea of pure contagion.

There are two methods for determining contagion. One of them is causality testing, while the other is dynamic conditional correlations based on multivariate GARCH models. The empirical research demonstrates that there is market contagion if cross correlations between markets rise during a crisis period. Moreover, the direction of the contagion is not reported by the correlation between two markets. As a result, the Granger causality approach is more suited for measuring spillovers. These two strategies are viewed as complementing one another in this notion.

2.2. LITERATURE REVIEW

The occurrence of volatility transmission between commodities markets is the subject of several research. In order to understand how volatility is transmitted among commodities, such as oil and gold, it is important to look at studies like those by Shafiee and Topal (2010), Todorova (2017), Bentes (2015), Zhang and Wei (2010), Yaya et al. (2016), Ewing and Malik (2013), Narayan and Narayan (2010), and Kumar (2017). In the context of structural breakdowns, Ewing and Malik (2013) studied the transmission of volatility amongst the prices of oil and gold. According to their findings, there was volatility transmission amongst them in both directions. The

efficiency of these markets was examined by Narayan and Narayan (2010) along with the history of the connection between the oil and gold futures markets. They came to the conclusion that when oil prices increased, investors bought gold as a hedge against inflation and that these markets were inefficient since oil prices could be used to predict gold prices and vice versa. Poshakwale and Mandal (2016) used conditional time-varying copula models to examine the asymmetric return correlations of stocks, bonds, real estate, and gold for the United States and found significant co-movements between each asset class.

Several studies (e.g., Baffes, 2007; Nazlıoğlu, 2011; Nazlıoğlu et al. 2013; Ji and Fan, 2012; Trabelsi et al. 2017; and Du et al. 2011) have examined how oil prices affect the prices of other commodities, especially agricultural ones. Nazlıoğlu (2011) investigated the connection between oil prices and agriculture prices. No short-term correlation between them could be found according to linear causality analysis. Nevertheless, using nonlinear causality analysis, the study points out that oil and agricultural commodity prices (with the exception of wheat) are linked in a way that is neither directional nor linear. Nazlıoğlu et al. (2013) also looked into the volatility spillover between them. They were unable to find a volatility spillover between the agriculture commodities and oil prior to the 2008 financial crisis, in contrast to other academics. Nonetheless, during the financial crisis of 2008, spillover of instability from oil prices to agriculture markets occurred. Ji and Fan (2012) examined whether the pre- and post-2008 financial crises had an impact on the prices of non-energy commodities. They discovered that the price of non-energy commodities was influenced by oil prices, although the impact was less noticeable prior to 2008 than it was thereafter. They also emphasized that the employed dollar index showed that commodity markets were mostly unaffected by the 2008 financial crisis.

2.3. EFFICIENT MARKET HYPOTHESIS

The availability of information is a concern for the efficient market theory. According to this theory, a market can be considered efficient if all accessible information is reflected in its pricing (Fama, 1970). The study of market efficiency can be traced back to Gibson (1889), Bachelier (1900), Mandelbrot (1963), Alexander

(1964), and Steiger (1964), among others (Sewell, 2011). The first efficient market was uncovered by Fama (1965a), who also conducted the first empirical investigation of stock prices that resembled a random walk. Fama (1965b) then tackled the generalized form of random walk, while Samuelson (1965) brought the idea of fair play to the field of financial economics, where he also studied the concept of martingale, which is also related to the random walk in a generalized form.

Roberts (1967) made a distinction between weak and strong efficiency types. Ultimately, the efficient market theory was divided into three types by Fama (1970): strong form, semi-strong form, and weak form. High form efficiency means that prices accurately reflect all information, including insider knowledge, that is both publicly and privately available. Investors shouldn't be able to consistently outperform the market in this scenario or generate returns above average. Both weak form and semi-strong form efficiency fall within the category of strong form efficiency. Prices are in semi-strong form when they reflect publicly available information, such as dividend announcements, dividend-yield ratios, book value-market value ratios, political and economic changes, and stock splits. Low form efficiency suggests that prices are an accurate reflection of past price data. Hence, utilizing weak form efficiency to predict future price swings offers minimal benefit. In other words, past price changes have no bearing on present or future price changes. Technical analysis becomes useless if the weak form efficiency is maintained. There is no historical data available to predict future price movements when the weak form is in effect.

The efficient market theory for international markets has been studied by numerous academics. Chan et al. (1997) investigated the weak form efficiency of 18 stock exchanges and 18 overseas markets individually or collectively. They discovered that most marketplaces were individually efficient, but very few were collectively efficient. Additionally, they argued that the absence of long-term swings in these markets made international diversification successful. Furthermore, Kan and O'Callaghan's evaluation of the foreign exchange markets in 2007 encompassed 10 Asia-Pacific countries, and they found that market efficiency was applicable for particular country pairs. In a similar vein, Kim and Shamsuddin (2008) investigated the efficiency of Asian stock markets. They discovered that the effectiveness of nations varied depending on their level of development by using novel multiple variance ratio

tests. Less developed emerging nations revealed inefficiency, while more developed developing nations showed a trend of poor form efficiency. Ito and Sugiyama (2009) used time as a different method of measurement for market inefficiency. They came to the conclusion that market efficiency in the US fluctuated throughout time. It was beginning to exhibit signs of inefficiency in the late 1980s, but it started to improve around 2000s.

The theoretical framework for this research is therefore provided by the efficient market hypothesis in the context of financial contagion. It is possible to assess the efficiency of these markets by analyzing the volatility transmission between the dry bulk and container freight markets. This is due to the fact that there shouldn't be any volatility transmission between markets in an efficient market. And if there is a transmission of volatility between these two markets, it will be possible to determine if it is a contagion or merely interconnection by comparing the pre and post COVID-19 crisis periods.

2.4. SHIPPING MARKET VOLATILITY

Despite the evident fragmentation of shipping freight industries such as container and dry bulk, these markets are not entirely separate (Stopford, 2009). From 2006 to 2007, it was discovered that several shipowners changed multipurpose ships that were formerly employed to transport containerized goods into dry bulk ships in order to earn more money due to the robust demand for dry bulk commodities (Hsiao et al. 2013). Moreover, it boosted interest in using containers to transport selected types of bulk materials. When it comes to commodities transported by bulk vessels and container vessels, the former transports primarily raw materials while the latter carries primarily finished or semi-finished items. As a result, the freight markets tend to follow one another somewhat gradually.

There are three prevalent hypotheses in shipping regarding the lead-lag relationship between container and dry bulk markets. Transport of Goods Hypothesis suggests that, when the market is exhibiting an upwards trend, container market will follow dry bulk market. The main reasoning behind this hypothesis is that the demand for raw materials will react first in the upwards trending economy, then it will indicate

change in demands for finished and semi-finished products. With this principle, in the downwards trending economy demands for finished and semi-finished products will react first, and then indicate change in demand for raw materials. Shipping Contract Hypothesis states that dry bulk contracts are often short-term contracts by nature. Therefore, dry bulk freight rates offer more flexibility in adapting to the current market trend (Kavussanos & Alizadeh, 2002). Price Formation Hypothesis assumes that, most of the dry bulk shipping industry operates under a structure of intense rivalry, where absence of large participants which have enough influence and market share to corner the market by setting the price of a TEU carriage, simply a homogeneous product. Since market structure of liner shipping market exhibits an oligopolistic structure, it is heavily influenced by large shipping alliances dominating the market (Alizadeh, 2001).

Table 3: The Lead-Lag Relationships of Three Hypotheses

Hypothesis	Downwards Trend	Upwards Trend
Transport of Goods	Dry Bulk Follows Container	Container Follows Dry Bulk
Shipping Contract	Container Follows Dry Bulk	Container Follows Dry Bulk
Price Formation	Container Follows Dry Bulk	Dry Bulk Follows Container

Source: Hsiao et al. 2013.

Bulk shipping, for instance, will be the first to adapt to occurrences in the economic climate while the market is expanding. This is because the market for raw materials will respond first to indicators of future increased demand for finished or semi-finished goods. In a downwards trending market, demand for finished goods is changes first, while decline in industrial output has a ripple effect on the demand for raw materials. This is because the demand for raw materials will react first in response to signs of future higher demand for finished or semi-finished goods.

Firstly, because the maritime industry requires great amounts of liquidity, freight volatility is a serious threat to maritime business and profitability. Relationship between the delay in returns and the initial delay and volatility transmission between freight markets can therefore be better understood by a number of maritime and financial market participants (Tsouknidis, 2016). As a result, they would be in a

position to decide wisely about portfolio diversifications, managing and hedging the risks associated with freight prices, and forecasting shipping freight rates.

Secondly, the effects of volatility on related freight markets can offer a useful mechanism for risk prediction, aiding stakeholders in the shipping industry's process for decision-making. In addition, it enhances the assessment of the freight derivatives' shipping costs (Tsouknidis, 2016).

Last but not least, there is undeniable proof that volatility spikes during crisis situations and extends to other markets, illuminating market correlations (Reinhart & Rogoff, 2008). Therefore, by analyzing and monitoring volatility transmission, regulators and investors can effectively implement risk-hedging strategies and uncover early warning signs of a marine freight market crisis.

In general, the ability of shipping market participants to create cash flow is significantly influenced by the freight rates. It arises from the fact that, in addition to a number of other distinguishing features, the shipping freight markets display significant volatility. Freight rates have a significant impact on international financial markets and are a reliable gauge of the state of the global economy (Alizadeh & Muradoğlu, 2014). As a result, it is vital that everyone involved in the maritime industry and capital markets to consider volatility transmission for freight markets and shipping in general.

The unpredictable and uncertain nature of the shipping industry has often been highlighted by a number of experts and market practitioners. Many studies have examined the turbulence and unpredictability of the shipping markets from different perspectives. Several research were first conducted in an effort to understand the trends in industry-wide volatility. Kavussanos and Visvikis (discussed global freight rates and pointed out that enormous freight volatility and high risk – high reward structure characterizes the shipping market. Adland and Cullinane (2006) on the other hand, underlined that short-term variations in freight rates could effortlessly result in bubbles and crashes. It would be advantageous for shipping carriers and businesses to comprehend the lead-lag interaction between container transportation and dry bulk freight markets and the volatility transmission between these two markets for hedging and managing freight rate risks. Because freight volatility will have an impact on profitability of the business and may endanger the company's very existence. Lee and

Ryu (2019) investigated the factors that contribute to freight market volatility in the US spot market. The authors analyzed the relationship between spot rates, fuel prices, and other macroeconomic indicators such as gross domestic product (GDP), industrial production, and employment. They suggest that fuel prices and macroeconomic conditions have a significant impact on freight market volatility. For illustrating the volatility structure of the markets, Memişoğlu (2018) used an EGARCH model on container freight markets, and Memişoğlu and Başer (2019) used an EGARCH model on dry bulk freight markets. Their findings show a negative leverage effect, high shock persistence, volatility clustering, and extremely high shock sensitivity on both segments. Ranjan et al. (2018) used bivariate analysis and EGARCH to examine the bunker markets' volatility. Both intermediate fuel oil (IFO) 380 and IFO 180 show a causal relationship between the two and both short- and long-term shock persistence. Using the GARCH-Baba Engle Kraft Kroner (BEKK) model, Hsiao et al. (2013) looked into how the volatility of freight moved across the bulk cargo and container shipping industries during the financial meltdown of 2008. During the financial meltdown, the dry bulk industry had some short-term spillover effects on the container industry, and vise - versa. Pouliasis et al. (2018) looked into the dynamics of stock price volatility and risk transmission in dry bulk, tanker, and container shipping industries. Their results showed significant correlation between notable losses and suggested an unequal transmission between industries.

Some research attempted to build or evaluate risk assessment and decision-making models that take industry-specific uncertainty into account in addition to studying market volatility trends. Nielsen et al. (2014) proposed a prediction model that took into account the market's unpredictability for container market and examined the influence of time frame and compatibility of observations on prediction. Bai and Lam (2019) used market ambiguity including product price arbitrage and bunker pricing to model the behavior of shipping destination selection. The emphasis on extremely big gas carriers shows how helpful the idea is for transport planning. The thirteen modeling methods were assessed by Rodrigues et al. (2019) for a maritime inventory route planning with uncertain travel duration and steady manufacturing and consumption levels. Findings indicated substantial benefits might be achieved by factoring in ambiguity during model formulation. Ivanov (2017) proposes a dynamic

supply chain management approach to managing supply chain risks. The author argues that this approach can help companies respond to changing market conditions, mitigate supply chain disruptions, and improve their supply chain resilience.

The literature also examines the factors that affect the extreme swings in value and a general air of unpredictability in shipping, as well as the volatility brought on by particular external shocks. Homan (2007) examined how the Maritime Transportation Security Act affected the stability of marine firms by employing a market model. According to the findings, the Act might reduce the financial risks faced by the firms and help maritime businesses raise financing. Chi and Cheng (2016) looked into how maritime trade movement of Australia to some of its most significant trading partners, notably China, were impacted by real income and exchange rate volatility. They came to the conclusion that the volatility of exchange rates had a considerable impact and a long-term impact on the volume of maritime exports. Holguín-Veras et al. (2016) examines the role of government in fostering freight transportation resilience and adaptation in response to disruptions. The authors argue that governments can play a significant role in enhancing the resilience of the freight transportation system through measures such as infrastructure investments, emergency response planning, and risk management strategies A system for classifying and analyzing shipping risks and uncertainties was offered by Thanopoulou and Strandenes (2017), who also estimated possible future ranges for the shipping industry through 2040. They suggested that in order to increase its resilience, the shipping sector must focus on the nature of effects. Lim et al. (2019) examine the impact of freight rate volatility on carrier capacity investment and service level. The authors develop a mathematical model to analyze the trade-offs between carrier capacity investment, freight rate volatility, and service level. They find that freight rate volatility can significantly affect carrier capacity investment and service level. To examine the impact of COVID-19 on the volatility of the dry bulk, clean, and dirty tanker markets, Michail & Melas (2020) used GARCH and Vector Autoregression (VAR) models. Their research showed that COVID-19 had secondary and tertiary effects on the stock market in addition to direct implications on the dry bulk and dirty tanker markets. Additionally, they pointed out that while the crude oil market did not exhibit a similar association, the dry bulk and clean tanker markets did show a strong correlation with the economy's demand side. In terms of

container ship traffic and port container throughput, Lam et al. (2021) assessed the turbulence and unpredictability of Singapore's container shipping market during the pandemic. As the main factors enhancing their greater resilience, they emphasized the significance of digitization and automation in the container shipping sector. The analysis of the literature finds that the studies on the connection between random shocks, such as the onset of a pandemic, and shipping market volatility are scarce. Therefore, analysis of the COVID-19-related volatility and uncertainty in the container shipping industry will be a key component of this thesis.

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CHAPTER THREE
RESEARCH METHODOLOGY

In this chapter, the empirical portion of the dissertation is laid out and the analysis process is introduced. In light of the introductory material and theoretical framework presented previously, the focus first shifts to the research questions. Then, the data sets that are the backbone of empirical research are introduced before digging deeper into them with descriptive statistics.

3.1. AIM OF THE STUDY

This dissertation aims to analyze the volatility transmission between container and dry bulk markets freight rates during COVID-19 pandemic through an Asymmetric BEKK-GARCH(1,1) model. By examining the volatility transmission between these markets, one can identify whether these markets are weak-efficient. This is since if there is a weak-efficiency, there should not be a volatility transmission effect among these markets. Also the nature of the volatility transmission among these two markets, if it exists, will be explored by analyzing the pre-pandemic period to determine if COVID-19 pandemic created a financial contagion for dry bulk and container freight markets. In this context, this thesis has the following research hypotheses and research questions.

H_1 = During COVID-19 volatility strongly transmitted from container freight market to dry bulk freight market.

H_2 = COVID-19 caused a financial contaigon between container freight market and dry bulk freight market.

H_3 = Both container freight market and dry bulk freight market do not have weak-efficiency.

Is there any volatility transmission and risk flow between container and dry bulk freight markets during COVID-19 pandemic?

The literature claims that despite the evident fragmentation of shipping freight industries such as container and dry bulk, these markets are not entirely separate. Since the Price Formation Hypothesis of shipping suggests that during an upwards trend in the market, as seen in COVID-19 period, dry bulk freight rates should follow container freight rates. In theory, this behavior should make the volatility in the container freight market to be transmitted to the dry bulk freight market. Therefore, first research question is formed in this regard.

Are container and dry bulk markets have weak-efficiency?

The efficient market hypothesis suggests that the prices in a market can be predicted by the historical prices. This situation can have dire consequences in a volatile market environment such as freight markets. By analyzing the volatility transmission structure of these markets, we can also determine if the past price volatilities have effect on the current volatilities of freight rates. If there is such occurrence, then we can deduce that there are no weak efficiency in the market. Although shipping market efficiency is discussed this in the past, this dissertation investigates the concept with a different method considering volatility transmission and risk memory.

Did COVID-19 cause a financial contagion between container and dry bulk freight markets?

In previous chapter, it is deduced that if there is a financial contagion there should be considerable increase in cross-market linkages following a crisis, because the transfer mechanism would be enhanced via the contagious effect of the said crisis. To this end, as far as to the author's knowledge there were no study yet to make this distinction for COVID-19 pandemics effects on freight markets.

3.2. ASYMMETRIC BEKK-GARCH MODEL

This dissertation employs an Asymmetric BEKK-GARCH(1,1) model proposed by Engle and Kroner (1995), which is optimized for measuring volatility transmission effects between two markets, in order to model the volatility transmission between container and dry bulk freight markets before and during COVID-19 pandemic. Our mean function is constructed as;

$$R_{i,t} = \mu_i + \Gamma_i R_{i,t-1} + \varepsilon_{i,t} \text{ where } i = m, a, d \tag{1}$$

Where $R_{i,t}$ and $R_{i,t-1}$ are the freight index return variables at times t and $t-1$, μ_i is the constant coefficient, Γ_i is the correlation coefficient, and $\varepsilon_{i,t}$ is the conditional variance coefficient. And the variance function is:

$$\varepsilon_{i,t}|\Omega_{t-1} \backsim D(0, H_{i,t}) \tag{2}$$

$$H_{i,t} = C_i'C_i + A_i'\varepsilon_{i,t-1}\varepsilon_{i,t-1}'A_i + B_i'H_{i,t-1}B_i + D_i'\xi_{i,t-1}'\xi_{i,t-1}D_i' \text{ where} \tag{3}$$

$$C_i = \begin{pmatrix} c_{i,11} & c_{i,12} \\ 0 & c_{i,22} \end{pmatrix}, A_i = \begin{pmatrix} a_{i,11} & a_{i,12} \\ a_{i,21} & a_{i,22} \end{pmatrix}, B_i = \begin{pmatrix} b_{i,11} & b_{i,12} \\ b_{i,21} & b_{i,22} \end{pmatrix}, D_i = \begin{pmatrix} d_{i,11} & d_{i,12} \\ d_{i,21} & d_{i,22} \end{pmatrix} \tag{4}$$

Here $\xi_{i,t-1}$ is represented as $\varepsilon_{i,t-1}$ if $\varepsilon_{i,t-1}$ is negative, and 0 if positive, which exhibits the impacts of asymmetric shocks. . $H_{i,t}$ is a conditional variance matrix and C_i is a lower triangular matrix with its inverse co-efficient matrix C_i'. A_i, A_i and D_i ($a_{i,mn}\ b_{i,mn}\ and\ d_{i,mn}$) matrices, which represent the diagonal parameters, measure the impacts of the historical shocks, volatility, and negative shocks of market m on the current conditional variance of market n, while A_i', B_i', and B_i' are their inversed forms. Meanwhile, Ω_{t-1} is the information set containing all information available up to time $t-1$.

3.3. DATA

The data used on analysis consists of weekly SCFI data published by the Shanghai Shipping Exchange and Baltic Dry Index (BDI) data published by the Baltic Exchange. SCFI is the most widely used index for sea freight rates for container shipping worldwide. This index has been calculated weekly since 2009 and shows the most current freight prices for container transport from the Chinese main ports, including Shanghai. BDI on the other hand is a shipping freight-cost index for dry bulk freight market. The BDI is a composite of the Capesize, Panamax and Supramax Timecharter Average indices. It is reported around the world as a proxy for dry bulk shipping stocks as well as a general shipping market bellwether.

In order to conduct a financial contagion analysis the data were split as pre-pandemic and pandemic periods. The split point is determined as 11 March 2020, the date which WHO announced COVID-19 as a global pandemic. The pre pandemic era is between 16 October 2009 – 6 March 2020. For this period, both series consist of 519 observations each. The pandemic time frame is between 13 March 2020 – 27 May 2022. Both freight index series include 115 observations each for the pandemic period. All of the mentioned data for the series were taken from Bloomberg Professional Terminal at Pamukkale University.

CHAPTER FOUR
VOLATILITY TRANSMISSION BETWEEN CONTAINER AND DRY BULK FREIGHT MARKETS

In this chapter, data preparation process, and preliminary tests, model estimation and post estimation diagnostics were conducted on WinRATS 9.2 Pro software while EViews 13 software package is used for graph generation. Once the data preparation is completed, empirical analyses are conducted and the results are discussed.

4.1. DATA PREPARATION

This dissertations data preparation process includes a check for normal distribution of the variables. The Jarque-Bera Test (Jarque and Bera, 1980), which is the gold standard for normalcy tests, is applied here. The formula for this statistical test is as follows:

$$JB = \frac{n}{6}[S^2 + \frac{1}{4}(K-3)^2] \quad (5)$$

Where K represents kurtosis and S represents skewness for n observations. Kurtosis, the third moment of a variable, takes the value of 3 and skewness, the fourth moment, takes the value of 0 for a normally distributed variable. The null hypothesis of the test is:

$$H_0 = K = 3 \; and \; S = 0 \quad (6)$$

Which assumes the series are distributed normally.

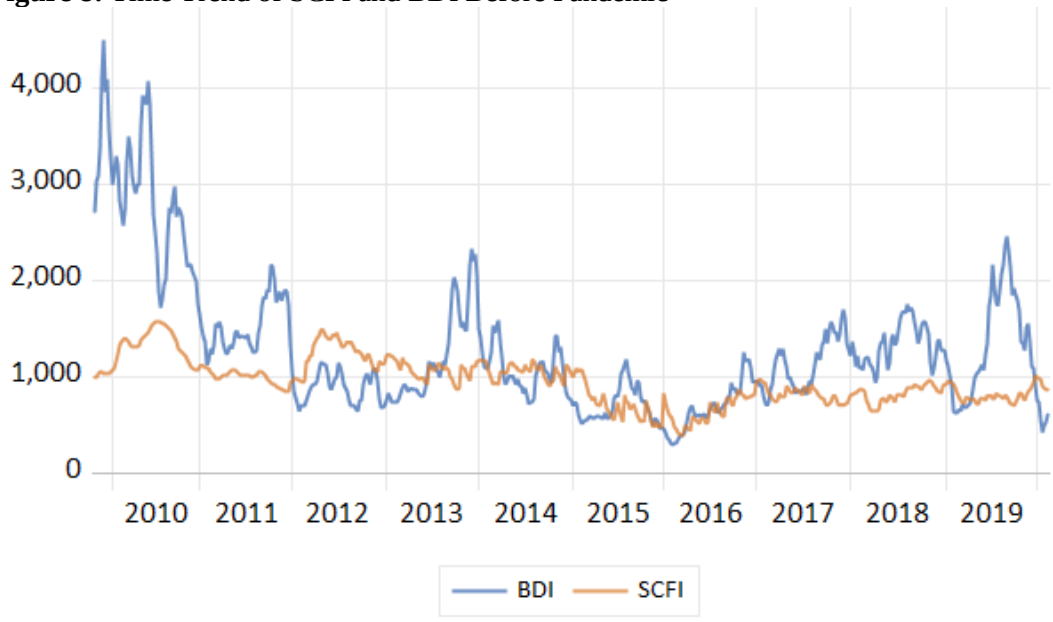
Table 4: Descriptive Statistics of SCFI and BDI Before COVID-19

	SCFI	BDI
Mean	961.1286	1301.961
Median	949.3300	1110
Maximum	1583.18	4507
Minimum	400.43	297
Std. Dev.	243.2939	724.2169
Skewness	0.305453	1.681827
Kurtosis	2.8726	6.073071
Jarque-Bera	8.4214	448.8904
Probability	0.014836	0.000000

Source: Generated by Author.

When Table 4 is inspected the high range between maximum and minimum index values and the enormity of the standard deviation of the index are first to be noticed. The standard deviation/mean ratios for SCFI (0.2531) and BDI (0.5562) quantifies this enormity. Also, when the skewness, kurtosis, and Jarque-Bera test statistics are inspected it can be said that the indices has excess kurtosis, skewed to the right and does not exhibit a normal distribution (Jarque and Bera, 1980).

Figure 8: Time Trend of SCFI and BDI Before Pandemic



Source: Generated by Author Based on Bloomberg (2022).

When Figure 8 is inspected closely, the volatile nature and cyclicality of freight rates are visually existent. While dry bulk freight market clearly appears as much more volatile than container freight market. This occurrence can be attributed to the fierce competition in dry bulk market compared to the oligopolistic nature of container shipping market.

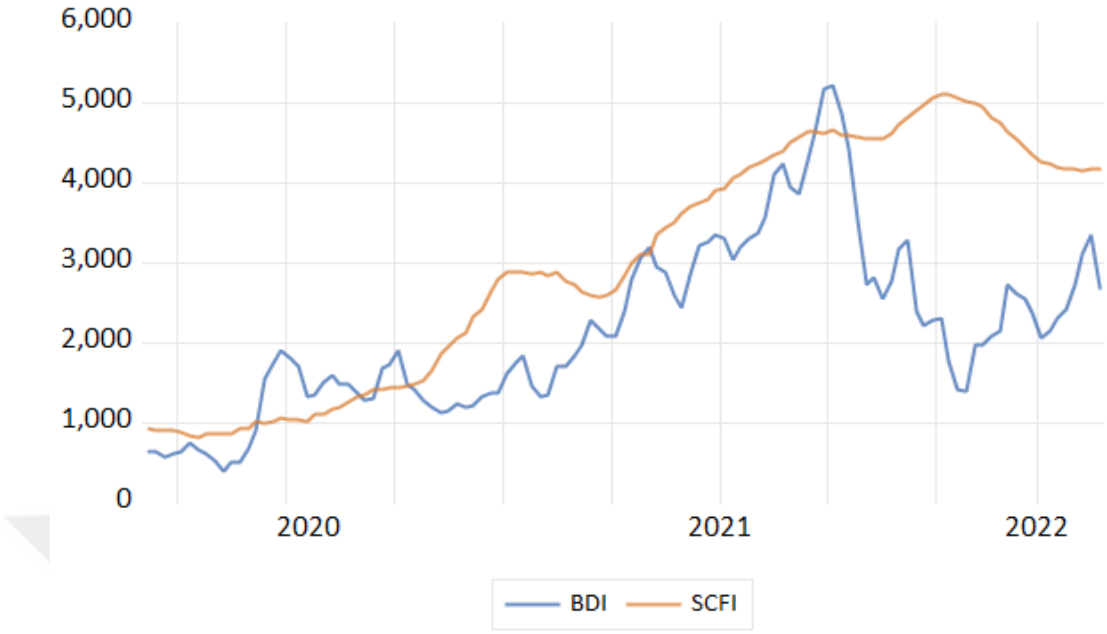
Table 5: Descriptive Statistics of SCFI and BDI During COVID-19

	SCFI	**BDI**
Mean	3003.095	2162.617
Median	2885.000	1977.000
Maximum	5109.600	5206.000
Minimum	818.1600	393.0000
Std. Dev.	1481.077	1086.487
Skewness	-0.174789	0.641206
Kurtosis	1.508344	3.041447
Jarque-Bera	11.24721	7.888523
Probability	0.003612	0.019366

Source: Generated by Author.

When Table 5 is inspected the high range between maximum and minimum index values, it can be seen that standard deviations of both indices grew exponentially during COVID-19 pandemic, which were already substantial before the pandemic. The standard deviation/mean ratios for SCFI (0.4931) and BDI (0.5023) shows this instability. Also, when the skewness, kurtosis, and Jarque-Bera test statistics are inspected it can be said that the index is fat-tailed, skewed to the sides and does not exhibit a normal distribution (Jarque and Bera, 1980).

Figure 9: Time Trend of SCFI and BDI During COVID-19



Source: Generated by Author Based on Bloomberg (2022).

When Figure 9 is inspected closely, since the declaration of COVID-19 as a global pandemic by WHO, overall freight rates exhibited an exponential increase. While dry bulk freight market clearly appears as more volatile, container freight market continued its steady increase. This occurrence can be attributed to the fact that container shipping industry consisting of an oligopolistic market composition, where freight rates are determined by the few and mighty shipping alliances, where they are more inclined to increase rates than decreasing them (Zhou et al. 2011). This situation fortifies the information asymmetry in the market, which is one of the main factors of non-existence of the market efficiency in the shipping freight markets, which we discussed in the previous sections.

4.1.1. Freight Index Returns

In order to employ a GARCH type modelling, first the raw series data of both pre-pandemic and pandemic era were converted into percentage return series by applying the natural logarithm differentiation equation.

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right) * 100 \quad (7)$$

Where P_t is the freight index value at time and R_t is the percentile freight index rate of return value at time t. After the conversion of SCFI and BDI to percentile return values, descriptive statistics were given at Table 6 and Table 7 and time trend graphs were given for the visual inspection at the Figure 10 and Figure 11 below.

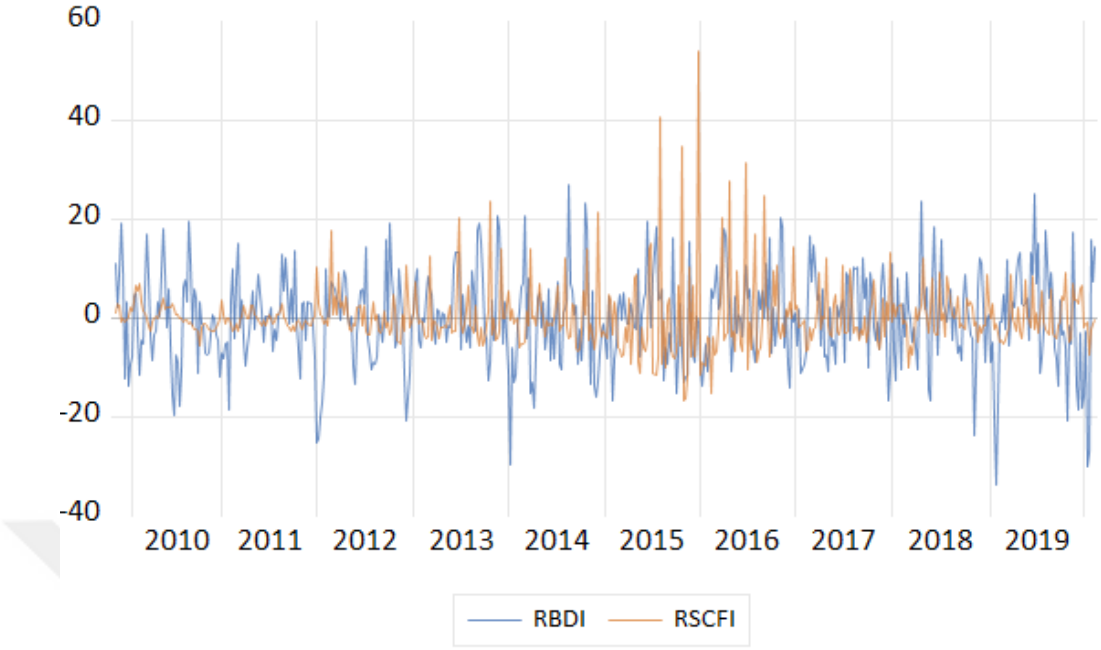
Table 6: Descriptive Statistics of RSCFI and RBDI Before COVID-19

	R(SCFI)	**R(BDI)**
Mean	-0.026627	-0.286960
Median	-1.038053	-0.143996
Maximum	53.80684	26.72035
Minimum	-16.81770	-33.86846
Std. Dev.	6.429427	9.235036
Skewness	2.784979	-0.099233
Kurtosis	18.66919	3.523600
Jarque-Bera	5968.825	6.767373
Probability	0.000000	0.033922

Source: Generated by Author.

When statistics of the series were examined, the mean returns of both Return SCFI (RSCFI) and Return BDI (RBDI) were negative for both of them before the pandemic. In addition, standard deviations show that dry bulk freight market fluctuations were larger compared to the fluctuations of the container freight market. Before the pandemic, the largest increase in container freight index returns were 53.8% in one week while dry bulk market experienced 26.7% increase. However when looking at the largest loss weeks dry bulk freight index returns decreased 33.9% while container market exhibited only 16.8% loss. This situation again points out to the oligopolistic nature of container shipping, where despite being much less volatile than dry bulk shipping, freight rates will experience greater magnitudes of increase during market upturns.

Figure 10: Time Trend of SCFI and BDI Percentage Returns



Source: Generated by Author Based on Bloomberg (2022).

Also, upon visual inspection it can be said that in both series extreme volatility is followed by extreme volatility and mild volatility is followed by mild volatility, in other words the volatility clustering visually obvious, more so in the dry bulk freight market than container freight market. In addition to that, when the skewness, kurtosis, and Jarque-Bera test statistics are inspected it can be said that the both indices exhibit excess kurtosis, skewed, and does not exhibit a normal distribution (Jarque and Bera, 1980).

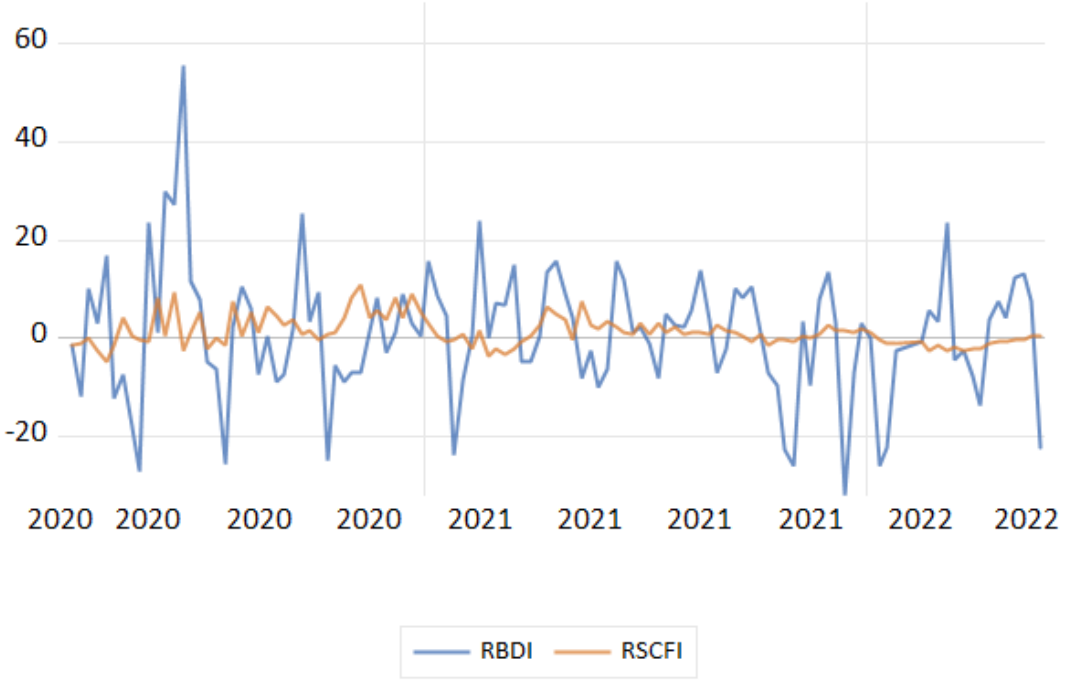
Table 7: Descriptive Statistics of RSCFI and RBDI During COVID-19

	R(SCFI)	R(BDI)
Mean	1.334630	1.266206
Median	0.730591	1.899155
Maximum	10.95791	55.46442
Minimum	-4.541441	-31.87212
Std. Dev.	3.006210	13.51546
Skewness	0.968335	0.365936
Kurtosis	3.771197	4.896752
Jarque-Bera	20.64081	19.63320
Probability	0.000033	0.000055

Source: Generated by Author.

When statistics of the series during COVID-19 pandemic were examined, the mean returns of both RSCFI and RBDI are positive for both returns. In addition, standard deviations show that dry bulk freight market fluctuations exhibited more than four times the magnitude compared to the fluctuations of the container freight market.

Figure 11: Time Trend of SCFI and BDI Percentage Returns During COVID-19



Source: Generated by Author Based on Bloomberg (2022).

Also, upon visual inspection it can be said that in both series extreme volatility is followed by extreme volatility and mild volatility is followed by mild volatility, in other words the volatility clustering visually obvious, more so in the dry bulk freight market than container freight market. In addition to that, when the skewness, kurtosis, and Jarque-Bera test statistics are inspected it can be said that the both indices are fat-tailed, skewed to the right and does not exhibit a normal distribution (Jarque and Bera, 1980).

4.2. STATIONARITY OF THE SERIES

In order to conduct a time series analysis, the series have to be free of unit root and stationary. If not they have to be stationarized by differencing them until there are no unit roots remaining. As a criterion for stationarity, a series' mean and autocovariances must be stable throughout time. If the following are true, then the Y_t process is stationary or covariance-stationary:

$$E(Y_t) = \mu \tag{8}$$

$$E[(Y_t - \mu)(Y_{t-j} - \mu)] = \gamma \text{ for all } t \text{ and } j \tag{9}$$

While descriptive statistics and visual gives a general idea about the stationarity of the series, unit root tests must be conducted to ensure the stationary assumption of the methodology. The series' stationarity is critical in a regression since the absence of this quality would result in spurious regression, which could lead to the incorrect conclusion that there is a relationship between variables when none actually exists. To this end, both Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were applied in this dissertation.

4.2.1. ADF Unit Root Tests

In the ADF Unit Root Test, the obtained test value is compared to its model with a constant consisting of;

$$\Delta y_t = \mu + \phi y_{t-1} + \sum_{j=1}^{p} \psi_i \Delta y_{t-j} + \varepsilon_t \quad (10)$$

Where μ is a vector of terms that are deterministic such as constant and trend. The autoregressive structure of the errors is approximated by the p-lagged difference terms, Δy_{t-j}, and the value of p is set such that the error term, ε_t, is serially uncorrelated. For determining the order of p lag selection Schwarz Information Criterion (SIC) formulated by Schwarz (1978) is employed. The SIC formulation is defined as:

$$SIC = k\log(n) - 2\log(\hat{L}) \quad (11)$$

Where $\hat{L}$ is the maximized value of the likelihood function, n is the number of observations, and k is the number of parameters estimated by the model.

Based on SIC, the lag length is given for RSCFI are 5 before the pandemic and 1 during the pandemic. With the same process with RBDI, the lag lengths are given as 0 before the pandemic and 4 during the pandemic. The ADF test's null hypothesis H_0, states that a unit root exists in the series, which in turn suggests that $\phi = 1$. A comparison is made between the acquired test statistics and the 1%, 5%, and 10% critical value levels to determine the validity of the hypothesis under investigation. The null hypothesis can be rejected at a certain level of significance if the value of the test statistics is smaller than the crucial value. If not, we must accept the alternative theory (Said and Dickey, 1984). As the Table 8 and Table 9 indicates that H_0 is rejected at all p-value thresholds, we can conclude that neither series has a unit root and are, thus, mean stationary both before and during COVID-19 pandemic according to ADF unit root test.

Table 8: ADF Unit Root Test Results Before COVID-19 Pandemic

	R(SCFI)	R(BDI)
ADF Test Statistic	-10.88887***	-14.98618***
1% level critical value	-3.442894	-3.442771
5% level critical value	-2.866965	-2.866911
10% level critical value	-2.569721	-2.569692

Note: *** refers to rejection of the null hypothesis for non-stationarity at 1%.
Source: Generated by Author.

Table 9: ADF Unit Root Test Results During COVID-19 Pandemic

	R(SCFI)	R(BDI)
ADF Test Statistic	-3.649023***	-5.808519***
1% level critical value	-3.491345	-3.495021
5% level critical value	-2.888157	-2.889753
10% level critical value	-2.581041	-2.581890

Note: *** refers to rejection of the null hypothesis for non-stationarity at 1%.
Source: Generated by Author.

4.2.2. KPSS Unit Root Tests

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is utilized with the ADF test since the two tests complement one another (Kwaitowski et al. 1992). The KPSS unit root test employs a reverse hypothesis in its interpretation, which means the null hypothesis H_0 is $\phi = 0$. Furthermore, the Newey-West covariance estimator automatically incorporates the bandwidth into the KPSS calculation, therefore the lag duration for the regression is not required (Newey and West, 1987). The test statistic is calculated with the formula below.

$$KPSS = \frac{\sum_{t=1}^{T} S_t^2}{s^2 T^2} \tag{12}$$

$$S_t = \sum_{i=1}^{T} \varepsilon_i \tag{13}$$

Where T is the effective sample size, s^2 is the Newey-West estimate of the long run variance and ε_i is the error term. Results of KPSS unit root tests are given at Table 10 for before COVID-19 and Table 11 for during COVID-19.

Table 10: KPSS Unit Root Test Results Before COVID-19 Pandemic

	R(SCFI)	**R(BDI)**
KPSS Test Statistic	0.034999***	0.037466***
1% level critical value	0.739000	0.739000
5% level critical value	0.463000	0.463000
10% level critical value	0.347000	0.347000

Note: *** refers that the null hypothesis for stationarity can not be rejected at 1%.
Source: Generated by Author.

Table 11: KPSS Unit Root Test Results During COVID-19 Pandemic

	R(SCFI)	**R(BDI)**
KPSS Test Statistic	-3.649023***	-5.808519***
1% level critical value	-3.491345	-3.495021
5% level critical value	-2.888157	-2.889753
10% level critical value	-2.581041	-2.581890

Note: *** refers that the null hypothesis for stationarity can not be rejected at 1%.
Source: Generated by Author.

As the Table 10 and Table 11 indicates that H_0 can not be rejected at all p-value thresholds, we can conclude that neither series has a unit root and are, thus, mean stationary both before and during COVID-19 pandemic according to KPSS unit root test.

4.3. HETEROSKEDASTICITY OF THE SERIES

In order to determine if the series are applicable for Autoregressive Conditional Heteroskedasticity (ARCH) type modelling, they must possess a heteroskedastic properties (Engle, 1982). To ensure this assumption both of the series for before and during the COVID-19 were tested against the homoskedasticity with ARCH-LaGrange Multiplier (LM) tests and the results are given at the Table 12 and Table 13 below.

4.3.1. ARCH-LM Heteroskedasticity Tests

The ARCH-LM test analyzes the model's squared residuals using past values of the squared residuals and a constant to determine whether heteroskedasticity exists (Engle, 1982). Moreover, the absence of any ARCH up to order q in the residuals e_t is the null hypothesis. If the real alternative is ARCH (q), it is asymptotically the strongest spatially (q). The regression analysis that follows is employed to test the null hypothesis that there is no ARCH (q):

$$e_t^2 = \hat{\delta}_0 + \sum_{s=1}^{q} \hat{\delta}_s \, e_{t-s}^2 + v_t \qquad (14)$$

The test statistic is asymptotically distributed as $\chi^2(p)$ stochastic process and has an LM interpretation. Results of ARCH-LM tests conducted on RSCFI and RBDI before COVID-19 are given in Table 12 and results during COVID-19 are given in Table 13.

Table 12: ARCH-LM Heteroskedasticity Test Results Before COVID-19

		R(SCFI)	**R(BDI)**
ARCH 1-12 Test	F-Statistic	6.688048***	3.381320***
	Prob.	0.0000	0.0001

Note: *** refers that the null hypothesis for homoskedasticity is rejected at 1%.

Table 13: ARCH-LM Heteroskedasticity Test Results During COVID-19

		R(SCFI)	R(BDI)
ARCH 1-12 Test	F-Statistic	3.117680***	1.988328**
	Prob.	0.0012	0.0368

Note: *** and ** refers that the null hypothesis for homoskedasticity is rejected at 1% and 5% respectively.
Source: Generated by Author.

According to the literature, lag durations were set at 12 under the assumption of homoskedasticity (Tsay, 2010; Zivot and Wang, 2003). Results of the ARCH-LM tests for both before and during COVID-19 periods reject the test's homoskedasticity assumption of H_0. Hence, it is proper to state that RSCFI and RBDI series in both periods have robust heteroskedastic structures suitable for ARCH type estimation.

4.4. MODEL SELECTION

After ensuring the stationarity and heteroskedasticity of the return series an Asymmetric BEKK-GARCH(1,1) model is specified in order to model the volatility transmission between container and dry bulk freight markets during COVID-19. The order of GARCH(p, q) model is selected based on Akaike Information Criterion (AIC) formulated by Akaike (1974), which suggest the optimal model is the one giving the minimum AIC statistic. The criterion graph of models are given in Table 14.

Table 14: Model Comparison Based on AIC Statistics

Model	AIC Statistic
BEKK - GARCH (1,1)	13.090*
BEKK - GARCH (1,2)	13.135
BEKK - GARCH (2,1)	13.161
BEKK - GARCH (2,2)	13.111

Note: * refers to the model with minimum AIC statistic
Source: Generated by Author.

4.5. FINDINGS

In light of the primary goal of the study — determining the volatility transmission between container and dry bulk freight markets during COVID-19 and whether the pandemic caused a financial contagion on these markets — and the findings of the preliminary test results obtained in previous section, Asymmetric BEKK-GARCH(1,1) models were developed for both time periods. The analyses are conducted on WinRats 9.2 Pro econometrics analysis software.

When it comes to the distribution of errors, the Gaussian normal distribution assumption simply can not handle the leptokurtosis that shows up in financial time series such as the freight index data. The extraordinary volatility of the market results in several instances of abnormally high and low rates of return. It is a resounding sign of error distributions with fatter tails. However, the conditional distribution of errors is under the assumption of t distributed in GARCH type models with a student-t distribution. The student-t conditional density function has the form $v > 2$ with mean 0 and variance 1 and degrees of freedom v.

$$\rho(z_{jt}|\Omega_{t-1}) = \Gamma\left(\frac{v+1}{2}\right)\Gamma\left(\frac{v}{2}\right)^{-1}\left((v-2)\pi\right)^{-\frac{1}{2}}\left(1+z_{jt}^{2}(v-2)^{-1}\right)^{\frac{-(v+1)}{2}} \qquad (15)$$

It is because v is also the level of leptokurtosis that this option was selected. Becoming akin to the Gaussian normal distribution, the student-t distribution approaches normality as $1/v$ approaches zero. When the student-t error distribution is used to estimate our models, degrees of freedom must be evaluated alongside the other parameters in the conditional variance equation.

4.5.1. Asymmetric BEKK-GARCH (1,1) Estimation Before COVID-19

Results for volatility transmission analysis for the period before COVID-19 pandemic are given at the Table 15.

Table 15: Asymmetric BEKK-GARCH(1,1) Model Estimation Results Before COVID-19

Variable	Coefficient	P-value	Variable	Coefficient	P-value
Mean (RBDI)	0.2793***	0.0000	B(1,1)	0.3592**	0.0432
Mean(RSCFI)	-0.1305	0.4062	B(1,2)	-0.0021	0.9363
C(1,1)	7.5182***	0.0000	B(2,1)	-0.0135	0.7541
C(2,1)	-0.0907	0.6742	B(2,2)	0.9453***	0.0000
C(2,2)	0.0000	0.9999	D(1,1)	0.5110***	0.0000
A(1,1)	0.2731***	0.0026	D(1,2)	-0.1006***	0.0001
A(1,2)	0.0112	0.6547	D(2,1)	-0.0785	0.6726
A(2,1)	-0.1378	0.2582	D(2,2)	0.6405***	0.0000
A(2,2)	-0.0096	0.8521			
Summary Statistics					
Log-Likelihood					-3419.1756
SIC					0.0000076

Note: ***, **, and * refers to significance at 1%, 5%, and 10% levels respectively.

Source: Generated by Author.

The results indicate that before the pandemic only in the dry bulk freight market, volatility is significantly affected by its past returns in the short run, with the coefficient of 0.2731. The transmission effects of the volatility indicate that there were no transmission between container and dry bulk markets before COVID-19 pandemic.

The results also reveal the long-run self-transmission effects of the volatility of the BDI and SCFI's past volatility on their current period volatilities, the values are respectively 0.3592 and 0.9453, which are both significant and confirms our initial suspicion on volatility clustering upon visual inspection. For the long-run mutual transmission effects of the past volatilities on the other markets current volatilities, the results indicate that there was no significant volatility transmission between the markets in the long-run before COVID-19. Therefore, it can be said that both indices did not have a significant continuous long-run or short-run volatility transmission between one another.

The results also point out both SCFI and BDI returns exhibited negative leverage effect, which means it was affected more by the bad news during COVID-19.

There is also a cross-market asymmetric response from dry bulk to container freight market with a coefficient of -0.1006. Additionally, when both dry bulk and container markets experienced simultaneous negative external shocks, these negative shocks clearly boosted the next week's asset return covariance for both markets before COVID-19.

4.5.2. Asymmetric BEKK-GARCH (1,1) Estimation During COVID-19

Results for volatility transmission analysis for the COVID-19 pandemic period are given at the Table 16.

Table 16: Asymmetric BEKK-GARCH(1,1) Model Estimation Results During COVID-19

Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
Mean (RBDI)	1.3914	0.4897	B(1,1)	0.7558***	0.0000
Mean(RSCFI)	1.2169***	0.0000	B(1,2)	0.0801***	0.0000
C(1,1)	2.5261*	0.0837	B(2,1)	-1.7415***	0.0000
C(2,1)	-0.3515	0.2155	B(2,2)	0.7093***	0.0000
C(2,2)	-0.0000	0.9999	D(1,1)	-0.1702	0.4436
A(1,1)	0.3896***	0.0001	D(1,2)	0.1054***	0.0089
A(1,2)	-0.0747***	0.0024	D(2,1)	1.7845*	0.0681
A(2,1)	0.9880**	0.0264	D(2,2)	-0.4044*	0.0573
A(2,2)	0.4637***	0.0000			
Summary Statistics					
Log-Likelihood					-729.1575
SIC					0.0000067

Note: ***, **, and * refers to significance at 1%, 5%, and 10% levels respectively.

Source: Generated by Author.

The results indicate that for both dry bulk and container freight markets, volatility is significantly affected by the past freight returns in the short run, respectively with values of and 0.3896 and 0.4637. The transmission effects of the volatility indicate that the past SCFI volatility has significantly and massively affected

the volatility of BDI with 0.9880 value during the COVID-19 pandemic. Although not nearly as strong in magnitude, volatility transmission from BDI to SCFI is also significant with -0.747 value.

The results also reveal the long-run self-transmission effects of the volatility of the BDI and SCFI's past volatility on their current period volatilities, the values are respectively 0.7558 and 0.7093, which are both significant and confirms our initial suspicion on volatility clustering upon visual inspection. For the long-run mutual transmission effects of the past volatilities on the current volatilities, the results indicate that SCFI's past volatility has a significant long run transmission effect on the BDI with -1.7415 value. Although not nearly as strong in magnitude, volatility transmission from BDI to SCFI in the long-run is also significant with 0.0801 value. Therefore, it can be said that both indices have significant continuous long-run bi-directional volatility transmission between each other.

The results also point out SCFI returns exhibited negative leverage effect, which means it was affected more by the bad news during COVID-19. There is also a bidirectional cross-market asymmetric response between container and dry bulk freight markets. Asymmetric transmissions being significantly stronger from SCFI to BDI with coefficient of 1.7845, compared to mere 0.1054 value of BDI to SCFI. Additionally, when both dry bulk and container markets experience simultaneous negative external shocks, these negative shocks clearly boosted the next week's asset return covariance for both of the markets during COVID-19.

4.6. POST ESTIMATION DIAGNOSTICS

To ensure the robustness of our results, the residuals of the estimation have to be free of any ARCH effects, in other words homoskedastic. To ensure this a multivariate ARCH-LM test proposed by Hacker and Hatemi-J (2006) is conducted on the residuals of our estimation.

4.6.1. Multivariate ARCH-LM Tests

According to Hacker and Hatemi-J (2006), assuming the vector of error terms is distributed with a matching $n\ x\ 1$ variance vector, σ_t^2, and zero covariance between the error terms. It is presumable that the variance vector will proceed as follows:

$$\sigma_t^2 = v + \rho_1 \varepsilon_{t-1}^2 + \cdots + \rho_m \varepsilon_{t-m}^2 + u_t \quad (16)$$

Where u_t is a vector of errors, each of whose components is taken to be white noise. Then an equation is analyzed in which the variables in Equation 16 are swapped out for their residual counterparts to test for ARCH effects:

$$\hat{\varepsilon}_t^2 = v + \rho_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \rho_m \hat{\varepsilon}_{t-m}^2 + u_t \quad (17)$$

Where, at time t, $\hat{\varepsilon}_t^2$ is the vector of squared residuals. The alternative hypothesis of multivariate ARCH effects of degree m is that at least one of the ρ_1 matrices ($i = 1, \dots, m$) is not a zero matrix, while the null hypothesis of no multivariate ARCH effects of degree m is H_0: $\rho_1 = \rho_2 = \cdots = \rho_m = 0$. To test the null hypothesis, this process utilizes the multivariate LaGrange Multiplier (MLM) test statistic.

$$MLM(m) = (T - \Delta)\log\left(\frac{|\Omega_R|}{|\Omega_U|}\right) \quad (18)$$

Where T is the sample size used to estimate the model and the denotation Δ indicates a parameter alteration. When the null hypothesis of no multivariate ARCH(m) is imposed, Ω_R is the estimated variance-covariance matrix for the error term vector in Equation 18. When the null hypothesis is not applied, Ω_U is the estimated variance-covariance matrix for the error term vector in Equation 18. The determinant of matrix Ω is represented by $|\Omega|$. The LM statistic has an asymptotically distributed χ^2 with $m\ x\ n^2$ degrees of freedom under the null hypothesis that there are no multivariate ARCH effects of order m. Results of the multivariate ARCH-LM tests

with lag orders of 2, 5, and 10 are conducted on our models' residuals are given in Table 17 for period before COVID-19 and in Table 18 for period during COVID-19.

Table 17: Multivariate ARCH-LM Test Results for Period Before COVID-19

Lags	**Statistics**	**Significance**
2	9.550	0.94562
5	33.620	0.89376
10	93.660	0.37495

Source: Generated by Author.

Table 18: Multivariate ARCH-LM Test Results for Period During COVID-19

Lags	**Statistics**	**Significance**
2	0.267	0.76620
5	0.249	0.93926
10	1.426	0.18153

Source: Generated by Author.

According to the multivariate ARCH-LM test results the null hypothesis of H_0, which suggests no multivariate ARCH effects on the residuals, or homoskedasticity, of models for both periods can not be rejected. Therefore, it is safe to state that models constructed for this dissertation are robust in their results.

CONCLUSION

The findings discussed above indicate that although container and dry bulk freight markets mutually transmit volatility amongst each other, the transmission from container market to dry bulk market is massively stronger. Therefore, it can be said that both indices have significant continuous volatility transmission effects both in the short-run and the long-run. Thus, the results support the Price Formation Hypothesis showing a lead-lag relationship between container and dry bulk freight markets. The results are also in line with previous research as they suggest dry bulk freight rates will follow container freight rates in the upwards trending economic situation, just like the massive increase in e-commerce volumes and international demand with the supply chain distortions increased the overall freight rates and created an enormous market upswing for shipping industry during COVID-19. Results may be an indicator of the existence of a leverage effect during COVID-19 period that negative shocks or bad news generate more volatility for container and dry bulk freight markets than the good ones indicating over-reaction. The explanation of this phenomenon may be the capital-intensity and capital structure of shipping companies since French et al. (1987) state that bad news increase the riskiness of the firms with higher debt to equity ratios and greatly increases the return volatility of the markets those firms operate in. This statement appears to be the explanation for the negative leverage effect of the container freight market, as studies conducted by Drobetz et al. (2013) over the financial structures of top 115 shipping firms and by Yeo (2016) over the financial structures of top 130 shipping firms and they pointed out an average of 1.74 debt-to-equity ratio for shipping industry.

The efficient market hypothesis suggests that, in case of weak efficiency, there should not be a volatility transmission between these markets, and past volatilities should not carry over to the future (Alomari, 2015, Chan et al. 1997). However, results indicate that there are strong mutual volatility transmissions between these markets, meaning they can be used as predictorial indicators for each other. Their volatility are also heavily effected by their own past volatilities, which means that historical freight values can be used to predict future freight values. Thus, pointing out that both container and dry bulk freight markets are inefficient.

Shipping markets practitioners should consider the volatility transmission effects stated, when they plan and impose shipping policies on either market to better foresee the effects of the policies upon the other market. However, from the perspective of EMH, regulators and policy makers should consider regulatory actions towards market efficiency in dry bulk and container freight markets, and future research may focus on efficiency guidelines for the shipping markets. For future recommendations this study can be extended by including other segments of freight market or employing one of the other shipping markets such as sale and purchase market. Also, our model as a byproduct of our estimation process, can be used as a base to generate the hedge ratio between container and dry bulk freight markets as fresh observations become available in the future.

When we recall the research hypotheses of this dissertation, which are:

H_1 = During COVID-19 volatility strongly transmitted from container freight market to dry bulk freight market.

H_2 = COVID-19 caused a financial contaigon between container freight market and dry bulk freight market.

H_3 = Both container freight market and dry bulk freight market do not have weak-efficiency.

All three hypotheses above can not be rejected due to the estimation results and reasons discussed above.

Originality of the Research

This dissertation differs from the studies in the literature in two different ways. Firstly, various studies tried to explain the volatility transmission mechanism amongst freight markets via variance causality and diagonal autoregressive methods. However, transmission effects mostly reside in off-diagonal matrices. Therefore, this study employs asymmetric full BEKK-GARCH parameterization to capture bivariate volatility transmission effects to highest extent.

Secondly, as far as the author's knowledge no study examining the volatility transmission between freight markets in the light of financial contagion has been encountered for COVID-19 period. Financial contagion refers to the spread of

financial disturbances or shocks from one market or institution to others, leading to a wider systemic crisis. The importance of understanding financial contagion lies in the fact that it can have significant adverse effects on the global financial system, economies, and individual investors. Thus, this study aims to examine the systemic effects of COVID-19 pandemic on container and dry bulk freight markets.

Practical Implications

Due to the risky nature of freight markets, understanding the transmission of volatility and its properties are crucial for all decision makers in maritime business environment. With the methodology used in this dissertation serving as a validation tool for EMH in the weak form, by giving investors an outlook for information asymmetry in container and dry bulk freight markets. Thus, they can deduce whether or not it is possible to gain extreme returns by analyzing historical freight rate and freight rate volatility data. As Stopford (2009) indicates, dry bulk freight market is considered a primary indicator for international trade and demand for raw materials whereas the price levels in container freight market is a direct reflection of international trade and demand for semi-finished and finished products. Due to these direct links of freight rates with the world economy, freight rates are considered as leading indicators for global economic climate (Açık and Başer, 2021). Thus, it is evident that freight rates are situated at the inner circle of global money stream (Alizadeh and Muradoğlu, 2014). Therefore, it is crucial for decision makers in the maritime industry and financial markets to grasp the dynamics volatility transmissions between container and dry bulk freight markets.

As financial contagion can cause a chain reaction of financial distress that can spread throughout the entire shipping market ecosystem. This can result in widespread financial instability, economic downturns, and the collapse of any of the four shipping markets, leading to significant losses for investors, businesses, and cargo owners. Shipping markets, just like financial markets and institutions, are highly interconnected, and the failure of one market such as freight market or a maritime institution can have a significant impact on others. Understanding the nature and extent of these connections is crucial to managing the risk of contagion and preventing its

spread. Financial contagion can easily spread across borders and affect economies worldwide. As the global economy becomes increasingly integrated, the risk of contagion has become more significant. Therefore, policymakers need to monitor global container and dry bulk freight markets closely and respond appropriately to prevent the spread of contagion. Financial contagion caused by the highly disruptive impact of COVID-19 can undermine investor confidence and trust in shipping markets, leading to a loss of faith in the stability of the maritime business ecosystem. This can have long-term negative effects on economic growth and stability both regional and global scales. Findings of our study, which proves the existence of time-varying freight rate volatilities, suggests a strategy of dynamically revising the assets to be included in a diversified container and dry bulk investment portfolio, as both returns and risks alter over time.

In addition, since the bivariate BEKK-GARCH model employed in this study directly specifies the conditional variance-covariance matrix of freight returns, investors can generate hedge ratios between container and dry bulk freight markets by feeding fresh observations to the model proposed in this dissertation to increase their efficiency in risk management. In summary, capturing the essence of disruptive effects of COVID-19 on container and dry bulk freight market volatility can have significant systemic effects on financial markets and institutions; it also highlights the interconnectedness of these two markets.

Limitations of the Study and Further Research

All studies have certain limitations and this dissertation is no exception to that rule. The first limitation is the usage of index values as a proxy of freight rates, rather than using actual freight rates. Although SCFI and BDI are considered best tools in regards to reflecting container and dry bulk freight rates in the market, using real freight rates could be more beneficial. The second constraint is that the due to publication rate of SCFI the analysis is conducted on weekly data. Usage of daily values would have yielded more sensitive results upon dissemination of volatility and explaining transmission effects.

For future recommendations, this study can be extended by including other segments of freight market or employing one of the other shipping markets. For example, dirty and clean tanker segment of freight markets or other markets such as sale and purchase markets could be taken account. In addition, rather than taking container and dry bulk freight markets as a whole, transmission effects can be tested on route basis and findings of those route based transmission effects can be compared to the results of this study. Also, our model as a byproduct of our estimation process, can be used as a base to generate the hedge ratio between container and dry bulk freight markets as fresh observations become available in the future.

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