Volatility Spillovers Among Selected Tourism Stock Indices

Oubayda El Rifai

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Approval of the Institute of Graduate Studies and Research

Prof. Dr. Ali Hakan Ulusoy
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy in Finance.

Prof. Dr. Nesrin Özataç
Chair, Department of Banking and Finance

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Doctor of Philosophy in Finance.

Asst. Prof. Dr. Nigar Taşpınar
Co-Supervisor

Prof. Dr. Nesrin Özataç
Supervisor

Examining Committee

1. Prof. Dr. Emrah İsmail Çevik
2. Prof. Dr. Salih Katırcıoğlu
3. Prof. Dr. Nesrin Özataç
4. Prof. Dr. Gülcay Tuna Payaslioğlu
5. Prof. Dr. Fatma Dilvin Taşkın Yeşilova

ABSTRACT

Volatility spillover is one of the most researched subjects in the finance literature due to its association with the transfer of risk between stock markets and portfolio management. The tourism sector has attracted significant attention from investors and scholars during the last two decades. Thus, the first concern of this thesis is to understand whether the volatility is transmitted among the major global tourism stock markets. Second, for portfolio diversification purposes, determine whether the effect of volatility transmission among tourism stock markets is temporary or persistent (long-lasting). For these purposes, Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) time- and frequency-domain methods are adopted. Results suggest that total spillovers of the tourism stock indices rose significantly during the pandemic. Turkey and Italy are net volatility spillover transmitters, and others are net volatility spillover receivers. The results also indicate that the effect of volatility transmission among tourism stock markets is temporary (short-lasting). The findings suggest that short-term investors and portfolio managers should avoid investing in the tourism indices in the short term.

Keywords: Volatility Spillovers, Stock Market, Covid-19

ÖZ

Hisse senedi piyasaları ve portföy yönetimi arasındaki risk transferi ile ilişkisi nedeniyle oynaklık yayılımı finans literatüründe en çok araştırılan konulardan biridir. Turizm sektörü son yirmi yılda yatırımcıların ve akademisyenlerin önemli miktarda ilgisini çekmiştir. Bu nedenle, bu tezin birincil amacı volatilitenin başlıca küresel turizm borsaları arasında yayılımını incelemektir. İkincisi, portföy çeşitlendirme amaçları için, turizm hisse senedi piyasaları arasındaki oynaklık yayılımı etkisinin geçici mi yoksa kalıcı mı (uzun süreli) olduğunu belirlemektir. Bu amaçla, Diebold ve Yılmaz (2012) ile Barunik ve Krehlik (2018) zaman ve frekans alanı yöntemleri benimsenmiştir. Sonuçlar, turizm hisse senedi endekslerinin toplam yayılmalarının pandemi sırasında önemli ölçüde arttığını göstermektedir. Türkiye ve İtalya net oynaklık yayılım vericileri ve diğerleri net oynaklık yayılım alıcılarıdır. Çalışmanın bulguları ayrıca turizm borsaları arasındaki oynaklık aktarımının etkisinin geçici (kısa süreli) olduğunu göstermektedir. Sonuçlar, kısa vadeli yatırımcıların ve portföy yöneticilerinin kısa vadede turizm endekslerine yatırım yapmaktan kaçınmaları gerektiğini göstermektedir.

Anahtar Kelimeler: Volatilite Yayılma Etkileri, Borsa, Covid-19

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
BRICS	Brazil, Russia, India, China, and South Africa
COVID-19	Coronavirus Disease
DAX	Deutscher Aktien Index
DCC-GARCH	Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity Model
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
FTSE	Financial Times Stock Exchange
G20	Group of Twenty Countries
G7	Group of Seven Countries
GARCH-BEKK	Bivariate Generalized Autoregressive Conditional Heteroskedasticity Model
GDP	Gross Domestic Products
GFEVD	Generalized Forecast Error Variance Decomposition
MENA	Middle East and North Africa
MIST	Mexico, Indonesia, South Korea, and Turkiye
Multivariate-GARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
S&P 500	Standard and Poor's 500
UK	United Kingdom
UNWTO	United Nations World Tourism Organization
US	United States
VAR	Vector Autoregressive Model

WHO	World Health Organization
WTI	West Texas Intermediate

Chapter 1

INTRODUCTION

1.1 Introduction

The rapid spread of information and the major deregulation and harmonization that resulted in the free movements of cash flow across and within markets are the best examples of how the information technology revolution has had a profound influence on the structure of financial markets in recent years (Gallo and Otrando, 2007). Due to market structure disparities, a shock in one market is swiftly conveyed to others, which stimulates market integration. This market integration results in volatility spillovers, also known as the transmission of volatility, across international markets or between local markets, which lead to a stronger linkage between stock markets (Su, 2020). Thus, researchers have become significantly interested in studying the volatility spillover that might occur across global markets or between different markets in the same country (Mensi et al., 2022; Billah, Balli, & Balli, 2022; Coksun & Taspinar, 2022; Li et al., 2021).

1.2 Volatility

Volatility may be defined as a measurement of the degree of uncertainty about the future price or return movements of assets. Rajhans and Jain (2015) defined volatility as a variable’s fluctuation over time. Volatility does not indicate the direction of the trend; however, it just measures the size of the trend. From a statistical perspective, volatility is a random variable's variance. Furthermore, in finance, volatility is a

measurement of the dispersion of asset prices or returns. In other words, it is the degree of fluctuation in an asset's price over time.

In the financial industry, understanding volatility is of crucial practical importance, particularly in the subfields of risk assessment, financial instrument pricing, and portfolio diversification. Asset return series, stock prices, and foreign exchange rates are all monitored by volatility in one way or another (Bonga, 2019). When volatility is high, securities companies are unable to employ their available capital in a free and efficient manner because they must hold a certain amount of cash equivalent investments. This is done with the intention of reassuring creditors and regulators. Whereas rapid shifts in volatility may lead either to tremendous gains or devastating losses (Kumar and Patil, 2016).

1.3 Volatility Spillovers

Over the last three decades, the financial connectedness of international stock markets has grown extremely significant. This globalization trend is primarily driven by the rapid advancement of technology and the growth in the movement of cash between nations (Badshah et al., 2018). Moreover, due to globalization, the volatility in asset prices in the financial market of one country may often have a delayed impact on the volatility of the financial markets in other countries, known as volatility spillover effects (Ke, Wang, and Murray, 2010; Zhong and Liu, 2021). According to Rigobon (2019), spillover is always present in the market, regardless of whether circumstances are favorable or unfavorable, and may be used to quantify the interdependence that exists inside the market. Thus, it is crucial for portfolio managers and policymakers to have a solid grasp of the interconnectedness of the various financial markets (Choi, 2022).

Furthermore, volatility also represents a proxy for risk (Li, 2021). The greater an asset's volatility, the greater the associated risk. Thus, the level of volatility spillover may be seen as the level of risk spread across markets. It is useful to define the nature of information transmission via empirical analyses of spillover effects. These analyses provide critical policy implications for investors to support international portfolio diversification options and risk management techniques. Enhanced risk of financial contagion is usually discovered during financial crises, which results in shocks being transferred from one stock market to another. As a result, the anticipated gains from the international diversity of the investors' portfolios will be negatively affected.

1.4 Volatility Spillover in the Stock Market

Many studies have investigated the importance of studying the volatility spillover in the stock market. In general, the study of volatility spillover may assist in better comprehending how information is conveyed from market to market. Becketti and Sellon (1989) pointed out that the importance of analyzing spillover may be attributed to the fact that it provides policymakers with a better understanding of the process of volatility transmission across local and foreign financial markets. Bensaida, Litimi, and Abdallah (2018) argued that the study of volatility spillover has direct repercussions for the development of optimum portfolios and measures to minimize damaging shock transmission. Moreover, Yadav, Sharma, and Bhardwaj (2022) investigated the potential for diversification by analyzing the spillover impact of the Chinese stock market on certain developing markets. They mentioned that opportunities to diversify investment portfolios internationally, rather than being confined to domestic markets, are abundant due to the connectedness of markets throughout the world. Finally, Sevinc (2022) examined the volatility spillover among MIST countries. Results showed that Mexico appeared as a risk transmitter to South

Korea and vice versa. Thus, the researcher concluded that investors could consider both stock markets while forming their portfolios.

1.5 Targeted Countries

Five countries were chosen to be the samples in this thesis. These five countries appeared among the top ten tourism destinations in 2020, according to the World Tourism Organization (UNWTO). The countries are as follows: China, Germany, the UK, Turkiye, and Italy.

1.5.1 China

China's economy has expanded rapidly since 1978, when openness and economic reforms were initiated, accompanied by a structural shift from agriculture to industry. Since that time, the gross domestic product (GDP) has increased rapidly. Nowadays, China occupies the second place in the global GDP ranking after the US (World Bank, 2021).

The main stock exchange markets in China are the Shanghai Stock Exchange, the Shenzhen Stock Exchange, and the Hong Kong Stock Exchange. These stock exchanges appeared among the top 10 stock exchange operators in the world by market capitalization (Statista, 2022). As of August 2022, the Shanghai Stock Exchange had 2167 listed companies, the Shenzhen Stock Exchange had 2737 listed companies, and the Hong Kong Stock Exchange had 2245, with market capitalizations of 6.78, 4.9, and 4.53 trillion dollars, respectively (Yahoo Finance, 2022). Figure 1 shows the market capitalization of the Chinese domestic firms for the period between 2006 and 2020. It is noticeable that the Chinese stock market has maintained a slight bullish trend between 2006 and 2018. However, after that, the trend increased sharply, and the market capitalization doubled in size between 2018 and 2020.

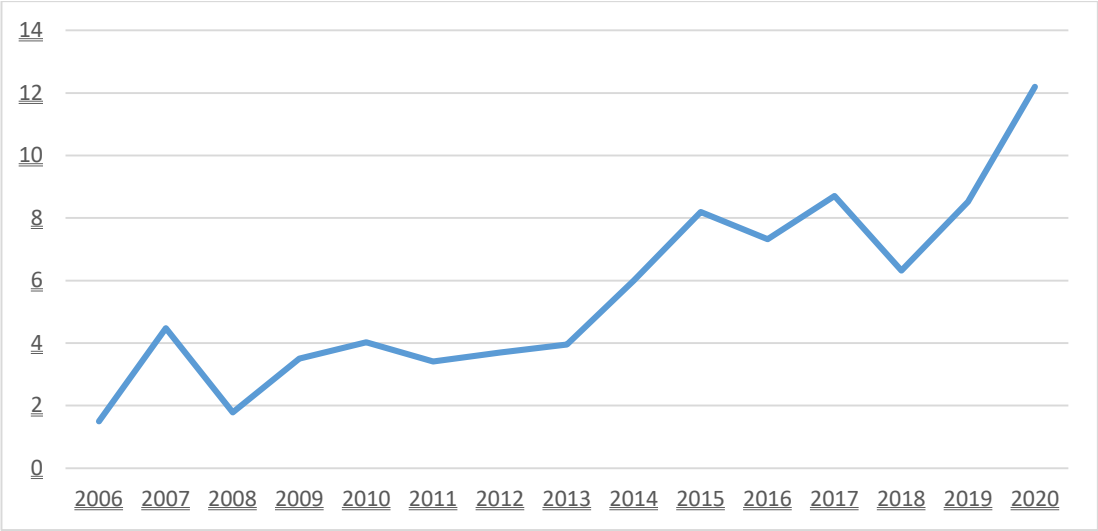

Figure 1: Chinese market capitalization of domestic listed firms (Trillion USD)
Data Source: World Bank

1.5.2 Germany

The German economy is the beating heart of the European economies (Bulmer, 2022). Germany has the highest Gross Domestic Product (GDP) in Europe and is fourth in the world (World Bank, 2021). Its GDP experienced an increase of 5.8% in 2021, and the highest percentage of nominal gross value added was recorded by the service sectors, at 69% (Destatis, 2022).

The Frankfurt Stock Exchange is the biggest of Germany's seven stock exchanges (Borse Frankfurt, 2022). Moreover, the DAX is a stock index that is traded on the Frankfurt Exchange and was created in 1988 with a base index value of 1000. The DAX is comprised of 30 of the biggest and most liquid firms that are headquartered in Germany, representing nearly 80 percent of the total market capitalization of German public firms. Figure 2 represents the market capitalization of the domestic listed firms in Germany. It is observable that a slight upward trend was maintained between 2010 and 2020.

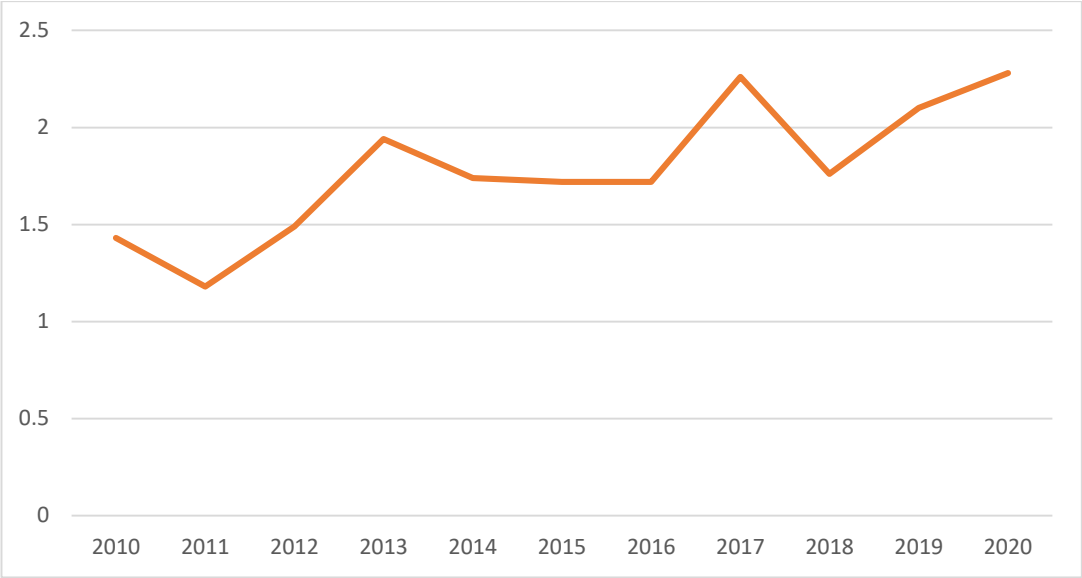

Figure 2: German's market capitalization of domestic listed firms (Billion USD)
Data Source: World Bank

1.5.3 United Kingdom

The United Kingdom has the world's fifth-largest gross domestic product (IMF, 2022). Due to the economic repercussions of the coronavirus pandemic, the UK's GDP shrank by a record 9.4 percent in 2020. However, the UK's economy managed to recover some of the losses in 2021, when data showed a 7.5 percent growth rate in the annual GDP (World Bank, 2022). Moreover, the UK's central stock exchange is the London Stock Exchange. According to market capitalization and the number of firms trading there, the London Stock Exchange is among the world's major securities exchanges (Rojo-Suárez et al., 2020). Figure 3 represents the market capitalization of London Stock Exchange for the period between 2010 and 2020. It is noticeable that the value of the listed companies on the London Stock Exchange has increased sharply after 2018 to reach 47.83 Billion GBP in 2020.

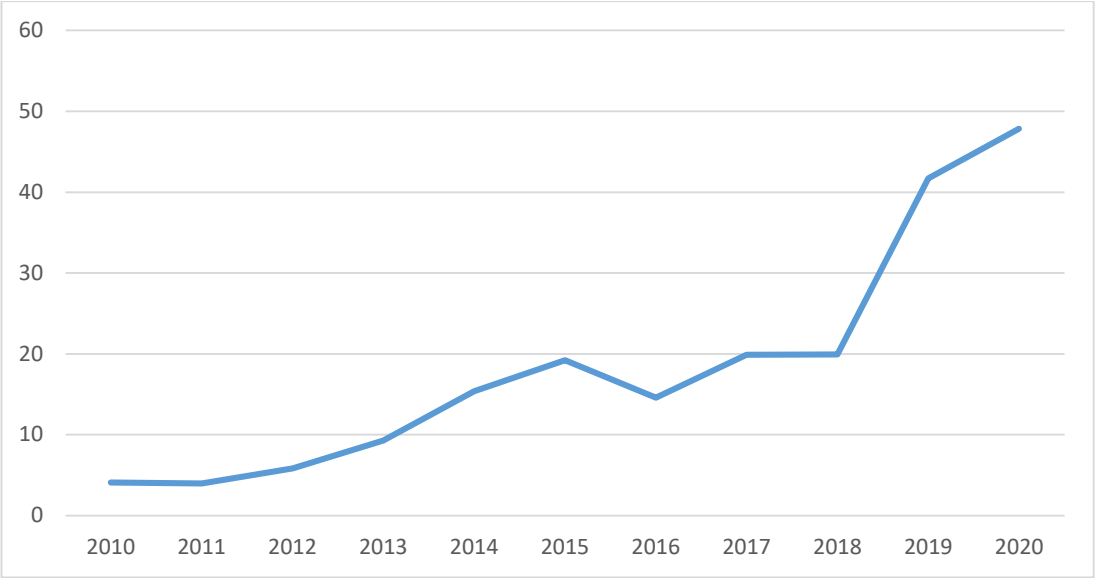

Figure 3:Market capitalization for London Stok Exchange (Billion GBP)
Data Source: World Bank

1.5.4 Turkiye

As COVID-19 regulations and restrictions were progressively reduced in Turkiye and abroad, the Turkish economy grew at the fastest rate among the G20 nations in 2021, where the GDP annual growth was 11%. As shown in Figure 3, regardless of the 2008 global financial crisis, Turkiye managed to maintain positive annual GDP growth over the last 20 years.

The only stock exchange in Turkiye is Borsa Istanbul. It has four markets: the equity market, the debt securities market, the derivatives market, and the precious metals market. Figure 4 illustrates the market capitalization of Borsa Istanbul in Turkish Lira (TL) and USD dollars between 2010 and 2022. The depreciation in the Turkish Lira has led to a wide gap between TL and USD market capitalization.

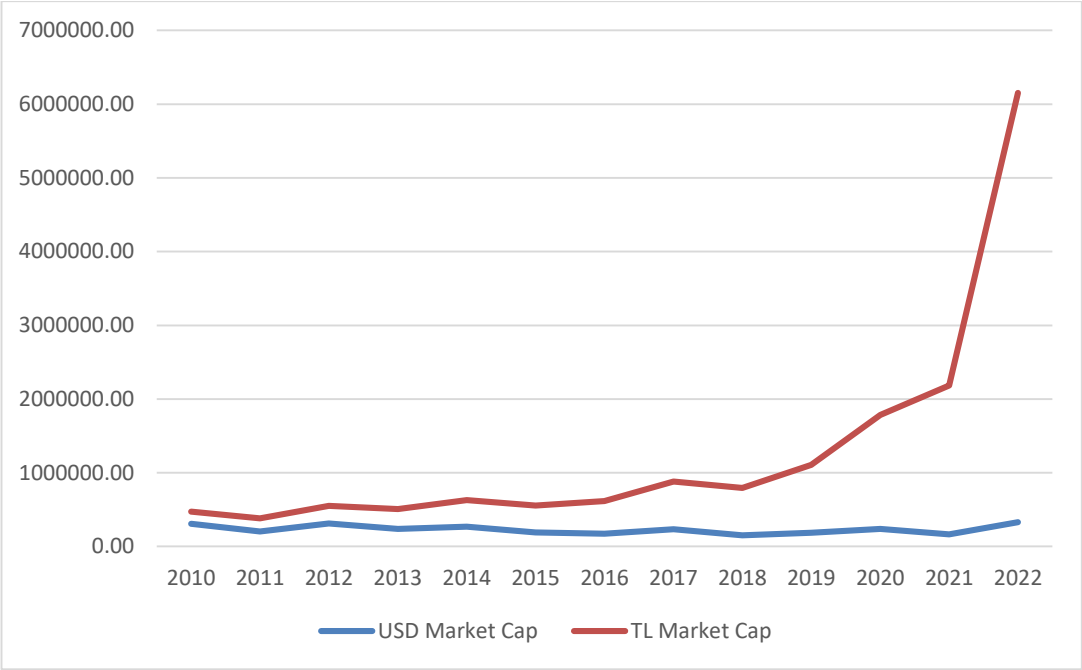

Figure 4: Market Capitalization of Borsa Istanbul (Billions Turkish Lira)
Data Source: Borsa Istanbul

1.5.5 Italy

Italy has the third-largest gross domestic product in the European Union after Germany and France (World Bank, 2022). The pandemic caused Italy's GDP to drop by 9 percent in 2020, but it was able to make up some of that loss and grow by 6.7 percent in 2021 (Istat, 2021).

The only stock exchange in Italy is the Milan stock exchange, which is officially known as Borsa Italiana. As of November 2022, Borsa Italiana had 408 domestically listed companies with a total market value of 663,510 million euros. Figure 5 shows the market capitalization of the listed companies in the Borsa Italiana for the period between 2010 and 2022. Over time, a slight bullish trend can be observed.

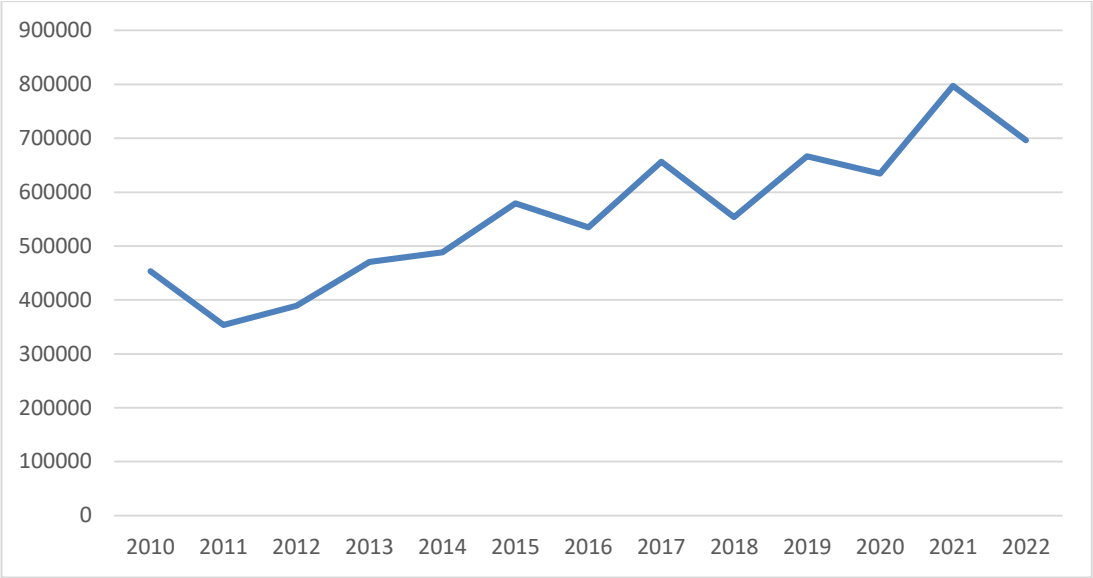

Figure 5: Market capitalization of listed companies in Borsa Italiana (Million Euro)
Data Source: Borsa Italiana

1.6 Aim of the Study

The COVID-19 outbreak was deemed a public health emergency of international concern by the World Health Organization (WHO). Enormous losses have taken place due to the quick spread of the virus, leaving the real economy to suffer. Losses took the form of shocks to the service and retail sectors, and production and operations are stagnant. The financial market has been exposed to significant shocks, including heightened liquidity tension, market panic, and other things (Wang et al., 2022). COVID-19 has had the greatest impact on the tourism industry (Yeh, 2021). Therefore, tourism stocks are highly affected due to uncertainties and shocks, which lead to fluctuations and volatility in tourism stocks' prices and returns. Investors and policymakers may react to uncertainties differently among countries due to cultural differences, preferences, and risk tolerance. Therefore, the level of volatility can differ among international tourism stock markets.

The aim of this thesis is, first, to understand whether the volatility is transmitted among the global tourism stock markets. Second, to understand whether the effect of volatility transmission among tourism stock markets is temporary or persistent (long-lasting) for portfolio diversification purposes. Diebold and Yilmaz (2012) connectedness methodology and Barunik and Krehlik (2018) time-frequency methodology are used in this study to reach this goal.

1.7 Contribution of the Study

Volatility connectedness among tourism stock indices at the aggregate level during the COVID-19 pandemic has not been studied enough in the current literature. For instance, Lin and Falk (2022) investigated the tourism stock market and its volatility in three Nordic countries using the Markov regime-switching model. Nhamo, Dube, and Chikodzi (2020) examined the impacts of COVID-19 on tourism-related stocks using event study methodology. Wu et al. (2021) used the event study method to look at how COVID-19 affected stock price changes in the Chinese tourism industry.

This research is, to the author's knowledge, the first to examine the volatility spillovers among five tourism stock indices of the top ten countries in terms of tourism destinations through the pre- and COVID-19 pandemic by adopting Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) methods. These countries are China, Germany, the United Kingdom (UK), Turkiye, and Italy, respectively.

1.8 Structure of the Study

This thesis is structured as follows: Chapter 1 is the introduction, and Chapter 2 sheds light on several parts of the literature on volatility spillover. Chapter 3 discusses the data and methodologies that are being followed in this study, while Chapter 4 exhibits

the findings of the study. Finally, Chapter 5 discusses the conclusion and recommendations.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

As a result of globalization and the growth of new information technologies, global financial market integration is steadily expanding. Thus, the interaction between financial markets has become more interdependent. This connection has been mostly discussed in terms of volatility spillovers. Volatility is the degree to which the price of an asset varies over time, while the volatility spillover effect describes how the volatility of one asset affects the volatility of another (Kocenda, 2018). Stock market volatility spillovers have been examined for the last three decades. This chapter will shed light on several parts of the literature on volatility spillover. First, the literature on volatility spillovers among international financial markets will be displayed. Second, the COVID-19 effect on the volatility spillovers of the stock market will be explored. Finally, subsectors and tourism volatility spillovers will be briefly discussed.

2.2 Volatility Spillover Effect in the Stock Market

In the literature, investigations on the interdependencies between global stock markets have focused on assessing how shocks from one stock market affect the performances and investor behavior of other markets. Eun and Shim (1989) analyzed nine major international stock markets. They found out that the US stock market had a unidirectional price spillover impact on other stock markets. Miyakoshi (2003) studied the size of the returns and volatility spillovers received by seven Asian countries from Japan and the US. The results showed that the Japanese stock market had a greater

impact on the volatility of Asian markets than the U.S. stock market. Liu (2016) studied the spillover effects, using the GARCH-BEKK approach, among the stock markets of the US, UK, Japan, and Hong Kong. He concluded that the returns of markets in the UK, Hong Kong, and Japan were constantly impacted by the prior performance of the US market.

Some studies focused on the volatility spillovers in developed countries (Jain and Sehgal, 2019; Savva, 2009; Xiao and Dhesi, 2010; Karunanayake and Valadkhani, 2011; Dajcman and Festic, 2012; Tsai, 2014; Akca and Ozturk, 2016; El Ghini and Saidi, 2017). Among the earliest, Hamo et al. (1990) examined the volatility spillovers among the stock market indexes of Tokyo, London, and New York. Volatility spillovers were observed from New York to London, New York to Tokyo, and London to Tokyo. Savva (2009) used the multivariate GARCH models to examine the transfer of price and volatility spillovers between the stock markets in the US and Europe. Daily closing prices were used for the period between August 3, 1990, and April 12, 2005. Results showed a bidirectional volatility spillover between the US and Europe. Moreover, not only do negative shocks in both markets increase the amplitude of the correlation between markets, but so does the occurrence of a combination of shocks with opposing signs. Karunanayake and Valadhani (2011) used weekly data (January 1992–June 2010) from four developed countries (Australia, Singapore, the United Kingdom, and the United States) to study the effects of market volatility transmission. Returns and volatility spillovers between the Slovenian stock market and six different European stock markets were studied by Dajcman and Festic (2012) using the DCC-GARCH model for the period between April 1997 and May 2010. Results showed a bi-directional volatility spillover between Slovenian and European stock markets. The

volatility spillover effects between the Moroccan stock market and four other developed countries (US, UK, Germany, and France) were studied by El Ghini and Saidi (2017). Their study covered the period between January 2002 and December 2012. They concluded that the 2008 global financial crisis reduced France and Germany's spillover effects on Morocco in the post-crisis period. Jain and Sehgal (2019) examined the volatility spillovers through the stock markets of eight developed economies between the years 2003 and 2014. Three sub-periods, prior to the 2008 global financial crisis, during the crisis, and post-crisis, were tested. Results indicated that there were no volatility spillover effects on the U.S. market from Australia and Canada during the crisis or from France, Germany, and Italy after the crisis.

On the other hand, many researchers have focused on the volatility spillover effect between developed and developing markets (Bein and Tuna, 2015; Abounoori and Tour, 2019; Cardona et al., 2017; Lee and Goh, 2016; Rejeb and Arfaoui, 2016; Qarni and Gulzar, 2018; Bala and Takimoto, 2017; Qian and Diaz, 2017; Vo and Tran, 2020; Yousaf et al., 2020; Yadav et al., 2022; Beraich et al., 2022). Bein and Tuna (2015) investigated the spillover effect on three emerging stock markets (the Czech Republic, Hungary, and Poland) through eight developed markets (Greece, Ireland, Portugal, Spain, Italy, the UK, Germany, and France) during the sovereign debt crisis period. As a result, a significant spillover effect from the eight European developed markets to the three emerging markets was noticed. Rejeb and Arfaoui (2016) examined the interdependence between Asian and Latin stock markets (emerging markets) from one side and the US and Japan (developed countries) from the other side. Geographical closeness and crisis periods were found to be closely associated with the transmission of volatility. Bala and Takimoto (2017) investigated the return volatility spillovers

from Nigeria, Japan, the UK, the US, Brazil, and China. Multivariate-GARCH models and their variants were adopted. The results confirmed the hypothesis, which states that a high level of volatility in the markets will lead to a high level of market correlation. Moreover, results suggest that the more developed a market is, the less it will be influenced by the shocks it has experienced in the past. Vo and Tran (2020) used the augmented EGARCH model to analyze the volatility spillovers from developed economies to emerging economies between August 2001 and December 2016. The stock market indices from the US and six Asian countries were used. The main findings revealed that the volatility in the US stock market has spread to Asian stock markets. The return and volatility spillovers between the US and China on one side and four emerging Latin American stock markets on the other were examined over the 2008 global financial crisis and the 2015 Chinese stock market crash by Yousaf et al. (2020). During 2008's global financial market, a bidirectional volatility spillover was observed between the US and the stock markets of Chile and Mexico, while it was unidirectional from China to Brazil. Furthermore, during the Chinese crash, bidirectional volatility transmission was noticed between the US and Mexican stock markets, as well as between the Chinese and Brazilian stock markets. Beraich et al. (2022) investigated the volatility spillovers between the American, European, and Chinese stock markets by applying the Diebold and Yilmaz (2012) methodology. Findings showed that although the volatility spillover index rose throughout the Russian-Ukrainian conflict, it did not reach the levels seen during the COVID-19 pandemic crisis.

Meanwhile, while most of the studies support the theory that volatility is more likely to spread from developed to emerging markets, Majdoub and Mansour (2014) and Li

and Giles (2015) came to a different conclusion in their studies. According to Majdoub and Mansour (2014), there was no conclusive evidence that US market shocks had any effect on Islamic emerging stock markets. Evidence suggested that market openness, unpreceded market shocks, and market integration are crucial for volatility transmissions across stock markets. Li and Giles (2014) noted strong bidirectional volatility spillovers between the US market and the Asian markets during the Asian financial crisis.

Furthermore, some other studies have focused on examining country groups, particularly those with rapidly developing economies (Bhar and Nikolova, 2009; Mensi et al., 2017; Alfreedi, 2019; Uludag and Khurshid, 2019; Panda et al., 2021; Yarovaya and Lau, 2016; Liu et al., 2017; Li, 2020; Su, 2020; Zhang et al., 2020; Sevinc, 2022; Habibi and Mohammadi, 2022; Yadav, Sharma, Aggrawal, and Bhardwaj, 2022). Su (2020) investigated the dynamic behaviors of volatility spillovers across all the G7 stock markets and identified the relevant elements that have an influence on those dynamic behaviors. Diebold and Yilmaz (2012), as well as Barunik and Krehlik (2018), were used. The US, Italy, and Canada were found to be transmitters of volatility spillovers, while France, Japan, the UK, and Germany were volatility spillover receivers. Moreover, the majority of volatility spillovers are driven by low-frequency components. Panda et al. (2021) used the Diebold and Yilmaz (2012) methodology to examine the volatility spillover among sixteen stock market indices, including BRICS countries and other developed markets. Daily data were collected for the period between August 2, 2002, and December 28, 2017. When the entire period is considered, the findings show that the net volatility transmitters are the US, the UK, and South Africa. Habibi and Mohammadi (2022) analyzed the degree to

which eleven different financial markets from MENA and four western economies are tied to one another. Weekly data were used for the period between 2005 and 2017, and Diebold and Yilmaz (2009, 2012, 2014) methodologies were employed. Findings showed that returns and volatility spillovers experienced a spectacular increase due to the global financial crisis.

Finally, some researchers expanded the literature and studied the volatility spillovers between the stock markets, natural gas, and oil (Ahmed, 2018; Xu et al., 2019; Hamdi et al., 2019; Tiwari et al., 2020; Shahzad et al., 2021; Tien and Hund, 2022; Costola and Lorusso, 2022; Jebabli, Kouaissah, and Arouri, 2022). Vardar, Coskun, and Yelkenci (2018) concentrated on five important commodity prices and stock market indexes from ten major developed and developing economies from 2005 to 2016. All of the examined markets showed evidence of a volatility spillover between stock and commodities returns. Furthermore, they observed that, across all nations, spillover impacts were particularly noticeable during the crisis and immediately after it. Moreover, Jebabli et al. (2022) studied the volatility spillovers among natural gas and oil prices and international stock market indices for the period 2000–2021. Their findings indicated that a new record of volatility spillover between energy and stock markets was achieved during the COVID-19 pandemic compared to the 2008 global financial crisis.

2.3 The Impact of COVID-19 Disease on the Stock Market

With the outbreak of the COVID-19 pandemic, global stock markets were exposed to significant uncertainty. Consequently, the majority of global stock market indexes have seen their worst one-day declines on record, and no industry has been spared. Contessi and De Pace (2021) offered statistical proof of the spread of instability from

the Chinese stock market to eighteen other stock markets, particularly between the last week of February and the first week of April 2020. Moreover, Wang et al. (2022) examined the volatility spillovers between major financial markets. Findings showed that the US and UK stock markets are net spillover senders, while the stock markets of China, Japan, and Hong Kong are net spillover receivers.

The effects of COVID-19 on the world economy or financial markets have been extensively studied in the literature (Caggiano et al., 2020; Mazur et al., 2021; Ramelli & Wagner, 2020; Zhang et al., 2020; Albulescu, 2021; Hasan et al., 2021; Guo et al., 2021; Tan et al., 2022). Al-Awadhi et al. (2020) used panel data to investigate the COVID-19 effect on the Chinese stock market. The total number of confirmed and death cases in COVID-19 had a significant negative impact on the stock returns of all companies, according to the findings. Moreover, an event study methodology was adopted by Singh et al. (2020) to scale the abnormal returns of the major stock indices in the G20 countries. It was concluded that the performance of stock markets throughout the globe was poor, and they all experienced negative returns. Ozili and Arun (2023) proved that because of the epidemic, stock market indexes fell because investors fled to more secure investments like government bonds.

Additionally, some studies examine the correlation between COVID-19 and the financial markets, often known as spillovers. A massive number of researchers examined the volatility spillovers across international stock markets (Adekoya and Oliyide, 2021; Corbet et al., 2021; Lin and Su, 2021; Hanif et al., 2021; Elsayed et al., 2022; Yousfi et al., 2021). Li (2021) conducted research to study the volatility spillover between developed and emerging stock markets. Ten countries were involved, and high-frequency data for the period between June 1, 2009, and August 28, 2020, was

used. Developed countries were found to be risk transmitters during the COVID-19 recession, while emerging countries were risk receivers. The same findings were concluded later in the study conducted by Wang et al. (2022). Akhtaruzzaman et al. (2021) investigate the form of the risk contagion that materialized between the Chinese and G7 countries' financial and non-financial firms. Umar et al. (2022) examined the connectedness of volatility between clean-energy stocks and fossil fuels by employing Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) methodologies. The findings revealed that most of the volatility spillovers among energy markets occur in the short term. The same methodologies were followed by Liu et al. (2022), who investigated the risk contagion among sixteen international stock markets during the COVID-19 epidemic. Daily data were used, and a total of 328 observations were investigated. Results showed that risk contagion lasts six to eight months in the international stock markets. Moreover, Choi (2022) investigated the volatility connectedness by employing the Diebold and Yilmaz (2012) methodology between Northeast Asian stock markets (South Korea, China, and Japan) and the US market. Findings showed that during some brief windows of time, Asian markets perform the function of net volatility spillover receivers. The United States has consistently been a net volatility spillover transmitter.

Furthermore, some studies investigated the volatility spillover effect among different local sectors during the COVID-19 period (Laborda and Olmo, 2021; Salisu et al., 2021; Shahzad et al., 2021; Su and Liu, 2021; Ahmad et al., 2022; Shigemoto and Morimoto, 2022; Choi, 2022). Laborda and Olmo (2021) applied Diebold and Yilmaz (2012) methodology to seven economic sectors in the US. They figured out that shocks are spread across the rest of the economy mostly via the technology and biotechnology,

energy, and banking and insurance sectors. Salisu et al. (2021) evaluated the return and volatility spillovers between tourism and health stocks for the period between January 2, 2018, and July 9, 2020. They discovered a significant negative bidirectional spillover in the health and tourism industries during the COVID-19 era. Shigemoto and Morimoto (2022) examined the volatility spillovers between different sectors in Japan for the period from 2014 until 2019. The findings of the Diebold and Yilmaz (2012) methodology revealed that the energy and banking sectors shifted from being risk receivers prior to COVID-19 to being risk transmitters after COVID-19.

COVID-19 is a systemic risk factor (Mensi et al., 2022). Moreover, there is a significant risk of contagion spreading from one stock market to another, which reduces the opportunities for diversification. Thus, the connection between stock markets and commodity markets has been heavily investigated during COVID-19 (Mensi et al., 2022; Sharif et al., 2020; Salisu et al., 2020; Mensi et al., 2021; Cheikh et al., 2022). Mensi et al. (2021) investigated the asymmetric return spillovers between gold futures and WTI crude oil futures from one side and ten different Chinese sector stocks by implementing the Diebold and Yilmaz (2012) methodology. Consumer discretionary sectors and industrials were found to be the primary transmitters and receivers of the volatility spillover. Furthermore, commodities appeared to be net receivers. The volatility spillovers between the S&P 500 and oil and gold were examined by Mensi et al. (2022). A 15-minute intraday data set was used, and the FIAPARCH-DCC model was applied. Results showed that, during the pandemic, gold had more diversification benefits than oil, and the pandemic made hedging more costly.

2.4 Sectoral Volatility Spillovers

Investigating sector-to-sector spillover effects is crucial since each sector has a unique economic connection. More recently, researchers have broadened their focus to include the effects of sectoral spillovers (Malik, 2022; Chen, Li, and Yao, 2022; Dang, Nguyen, and Vo, 2022; Bui et al., 2022). Yin, Liu, and Jin (2020) investigated the volatility spillovers between the industries on the Shanghai Stock Exchange for the period between 2009 and 2018. The empirical findings demonstrated that the development process of spillover effects across sectors correlates to certain occurrences in the political and financial markets. Investors can avoid these events by exercising caution when allocating their assets. Shen et al. (2022) examined the volatility spillovers between 28 sectors in China by adopting the Diebold and Yilmaz (2014) methodology. Daily closing index prices were used for the period between January 4, 2000, and December 31, 2019. Seventeen sectors were found to be risk transmitters, while the rest were risk receivers. They also discovered that during the most dangerous events (global financial crisis, Chinese stock market crash), connectedness measures increased.

Finally, Nhamo et al. (2020) examined the impacts of COVID-19 on tourism-related stocks using event study methodology. Wu et al. (2021) studied the impact of COVID-19 on stock price movements in the Chinese tourism industry using the event study method. Katircioglu and Katircioglu (2022) examined the interactions between the stock performance of tourism firms in Turkey. Lin and Falk (2022) investigated the tourism stock market and its volatility in three Nordic countries using the Markov regime-switching model. Findings showed that online gambling firms performed well during COVID-19. However, international transportation companies, hotels, and

restaurants had a poor performance. Moreover, Khanna, Sharma, and Pant (2022) investigated the stock price volatility of Indian tourism firms during the earliest wave of COVID-19. Findings confirmed that the market's first reaction is increased volatility in stock prices, but as investors process the news, volatility declines, even though the disease continues to spread. Hadi, Naeem, and Karim (2022) studied the volatility spillovers between the US tourism subsectors for the period between 2008 and 2021. They found that the recreational, transportation, and hotel industries are net transmitters of volatility to other US subsectors.

Based on the preceding, previous studies examined the volatility spillovers in the global and local stock markets at local and regional levels. Our study will enrich the current literature by investigating the volatility spillovers among selected global tourism stock indices by adopting Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) time- and frequency- domain methods.

Chapter 3

DATA AND METHODOLOGY

3.1 Data

This study examines the volatility spillovers among selected tourism stock indices during the COVID-19 period. Table 1 shows the list of countries for which data on tourism sector indices were available for 1554 days, as well as variable definitions. These five countries; China, Germany, the UK, the US, Turkiye, and Italy, were listed among the top ten tourism destinations in 2020, according to the World Tourism Organization (UNWTO). This study considers the pre-COVID-19 period (September 9, 2015, to December 31, 2019) and the COVID-19 period (January 1, 2020, to January 28, 2022). The daily closing prices for the included tourism sector indices were extracted from Thomson Reuter's Data Stream. Furthermore, return series are calculated as $100*\ln(P_1/P_0)$ where P represents daily stock prices. Finally, the absolute values of the return series are taken to calculate the volatility of each variable.

Table 1: Variable Definitions

Variable name	Tourism Stock Index	Data Type
China	FTSE China Travel & Leisure	Daily Closing Prices
Germany	FTSE Germany Travel & Leisure – Price Index	Daily Closing Prices
UK	FTSE 350 Travel & Leisure	Daily Closing Prices
Turkiye	BIST Tourism	Daily Closing Prices

Italy	FTSE Italia All share Travel & Leisure	Daily Closing Prices

3.2 Methodology

The first concern of this study is to understand whether the volatility is transmitted among the global tourism stock markets. Second, to understand whether the effect of volatility transmission among tourism stock markets is temporary or persistent (long-lasting) for portfolio diversification purposes. Thus, this study employs Diebold and Yilmaz's (2012) connectedness methodology and Barunik and Krehlik's (2018) time-frequency methodology. The Diebold-Yilmaz approach is founded on the concept of forecast error variance decomposition within the generalized VAR framework. However, the spectral representation of variance decompositions is added by Barunik and Krehlik (2018) to develop the Diebold-Yilmaz technique.

3.2.1 Diebold and Yilmaz (2012) Method

The main goal of this study is to investigate the volatility spillovers among specific tourism stock indices. So, to reach our goal, we use the variance decomposition method, which was first shown by Diebold and Yilmaz (2009) and then made more general by the same authors in Diebold and Yilmaz (2012). Diebold and Yilmaz (2009) paper had some methodological and substantive limitations. First, relied on the Cholesky-factor identification of VARs, and thus the resulting variance decompositions can be dependent on variable ordering. Second, it focused only on the cumulative effects of the spillovers. Thus, Diebold and Yilmaz (2012) used a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering, and they clearly included directional volatility spillovers.

Generalized forecast error variance decomposition (GFEVD), which is the proportion of the forecast error variance of the variable i due to the shocks from the variable j, from Koop et al. (1996) and Pesaran and Shin (1998), is used for a steady VAR(p) model. It can be calculated as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i' A_h \Sigma A_h' e_i)} \quad (1)$$

Where Σ is the covariance matrix for the error vector ε, σ_{jj} indicates the standard deviation of ε_j of the j^{th} equation, A_h indicates a n × n matrix of moving average coefficients corresponding to the lag h. $\theta_{ij}^{g}(H)$ constitutes the generalized variance decomposition matrix. Moreover, each matrix entry is normalized and named volatility spillovers from variable *j* to variable *i* to compare the pairwise connectedness of any two markets.

$$C_{i\leftarrow j}(H) = \tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \quad (2)$$

It weighs the sum share of volatility shocks from market *i* transmitted to other markets in the gross forecast error variance for each variable.

It is also essential to investigate the direction in which spillover effects travel, both away from and toward a particular market. We can find the directional connectedness from market *i* to all other markets as:

$$C_{\cdot\leftarrow i}(H) = \frac{\sum_{j=1,j\neq i}^{n}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{n}\tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \quad (3)$$

Similarly, we can find the volatility spillovers from all other markets to market *i* as:

$$C_{i\leftarrow\cdot}(H) = \frac{\sum_{j=1,j\neq i}^{n}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{n}\tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \quad (4)$$

The net directional connectedness, also known as "Net volatility spillover", can then be examined by taking the difference between the total volatility shocks which was transmitted and received from all the markets included in the sample, as shown in equation (5):

$$C_i(H) = C_{\cdot \leftarrow i}(H) - C_{i \leftarrow \cdot}(H) \quad (5)$$

A negative net volatility spillover indicates that market *i* is a volatility spillover receiver, while a positive net volatility spillover indicates that the spillover effects from market *i* are conveyed to all other markets.

Adding up all the non-diagonal $\tilde{\theta}_{ij}^{g}(H)$, total volatility spillover index will be acquired as follows:

$$C(H) = \frac{\sum_{i,j=1,i\neq j}^{n} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{i,j=1,i\neq j}^{n} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \quad (6)$$

The total volatility spillover index indicates the percentage of the contribution of shocks to volatility spillovers among the tourism stock indices in the following countries: China, US, UK, Germany, Turkiye, and Italy.

3.2.2 Barunik and Krehlik (2018) Method

Using the method introduced by Barunik and Krehlik (2018), the technique used to measure the frequency dynamics of spillover and the spectral presentation of variance decomposition will be discussed, taking into accounts the different kinds of frequency dynamics, whether they are short-term, medium-term, or long-term.

The Fourier transform is used to measure connectedness in the frequency domain. Furthermore, the frequency response function is $\psi_h : \psi(e^{-i\omega}) = \Sigma_h e^{-i\omega h} \psi_h$ where

$\boldsymbol{\psi_h}$ can be presented as a Fourier transform of the coefficients, with $i = \sqrt{-1}$. The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ is shown as:

$$(f(\omega))_{jk} = \frac{\sigma_{kk}^{-1}|(\boldsymbol{\psi}(e^{-i\omega})\Sigma)_{jk}|^2}{(\boldsymbol{\psi}(e^{-i\omega})\Sigma\boldsymbol{\psi}'(e^{+i\omega}))_{jj}} \tag{7}$$

$(f(\omega))_{jk}$ represents the portion of the *jth* variable's spectrum at a specific frequency ω based on the shocks in the *K*th variable. To obtain the impact of any variable at a given frequency, we can measure $(f(\omega))_{jk}$ with $\boldsymbol{\Gamma}_j(\omega)$ as follows:

$$\boldsymbol{\Gamma}_j(\omega) = \frac{(\boldsymbol{\psi}(e^{-i\omega})\Sigma\boldsymbol{\psi}'(e^{+i\omega}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\boldsymbol{\psi}(e^{-i\lambda})\Sigma\boldsymbol{\psi}'(e^{+i\lambda}))_{jj}d\lambda} \tag{8}$$

Where $\Gamma_j(\omega)$ indicates frequency share of the variance of the *j*th variable. The scaled GFEVD on the frequency band d = (a,b): a,b $\in$ $(-\pi, \pi)$, $a < b$ is presented as follow:

$$(\tilde{\theta}_d)_{j,k} = (\theta_d)_{j,k} / \sum\nolimits_k (\theta_\infty)_{j,k} \tag{9}$$

Where $(\theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)(\tilde{f}(\omega))_{j,k}d\omega$ indicates generalized variance decompositions on frequency band *d*, $(f(\omega))_{j,k}$ is generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$, then $(\theta_\infty)_{j,k} = \sum\nolimits_{d_s} (\theta_{d_s})_{j,k}$

Finally, the frequency connectedness (total spillover) on the frequency band d can be calculated as:

$$S^F(d) = 100 \times \left(\frac{\Sigma\tilde{\boldsymbol{\theta}}(d)}{\Sigma\tilde{\boldsymbol{\theta}}(\infty)} - \frac{Tr\{\tilde{\boldsymbol{\theta}}(d)\}}{\Sigma\tilde{\boldsymbol{\theta}}(\infty)}\right) \tag{10}$$

Where $\Sigma\tilde{\boldsymbol{\theta}}(d)$ is the aggregate of all elements of the $\tilde{\boldsymbol{\theta}}(d)$ matrix. Short-term, medium-term and long-term connectedness will be reached if we alter the intervals for frequency band d.

Chapter 4

EMPIRICAL RESULTS

4.1 Descriptive Statistic

The descriptive analysis of our sample is presented in Table 2. In terms of skewness, all the countries are positively skewed except for Turkiye, which is negatively skewed. China and Germany had the highest skewness, which implies that the largest recognized volatility occurred in these two countries. The excess kurtosis values of all volatility series are above 0, indicating that they are leptokurtic. Moreover, the Jarque-Bera normality test was checked under the null hypothesis that the series are normally distributed. As a result, the null hypothesis is rejected, and the volatility series are not normally distributed. Furthermore, because the Diebold and Yilmaz (2012) method is based on the VAR model, our data must be stationary. Thus, the Augmented Dickey-Fuller (ADF) test was checked, and the null hypothesis was rejected. The null hypothesis states that the data is not stationary. The intercept and time trend with lag 2 model is adopted. Finally, we tested the serial correlation of the variables by employing the Ljung–Box serial correlation test. The null hypothesis states that the data is not serially correlated. Results indicate that our variables are serially correlated.

Table 2: Descriptive statistics of the return series

Variable	Germany	UK	Turkiye	China	Italy
Minimum	-79.11	-16.62	-16.93	-14.53	-22.43
Maximum	76.26	23.97	10.30	9.16	16.91
Mean	-0.01	0.01	0.13	0.05	-0.001

Std. Dev	3.85	1.90	2.34	2.41	2.00
Skewness	2.57	0.53	-0.41	4.76	0.005
Excess Kurtosis	11.52	1.58	16.14	3.16	2.75
JB	135.99*	2.71*	254.40*	32.153*	7.38*
Ljung–Box	47.23*	14.93**	1.73	34.01*	15.06
ADF	-8.93*	-9.60*	-8.45*	-7.16*	-9.76*

* Indicates that H0 is rejected at 1%, while ** indicate that H0 is rejected at 5%

4.2 Diebold and Yilmaz (2012) Results

4.2.1 Static Analysis

We first used Diebold and Yilmaz's (2012) test to determine the time-domain spillover impact of tourism stock indices. Table 3 presents time-invariant volatility transmission results among the tourism stock indices (Diebold and Yilmaz 2012 test). The figures in each row, labeled “To”, show the percentages of volatility spillover that have been transmitted from one market to other markets. Moreover, the figures in each column, labeled “From”, represent the percentages of volatility spillover that have been received from other markets, including its own. Finally, to calculate the net volatility spillovers, we compute the differences between the rows and columns (to - from).

The total volatility spillover effect in the time domain approach was 25.46%. It is noticeable that the most transmitted volatility spillovers among the considered markets are from Italy to the UK (43.58%), while the least transmitted volatility spillovers are from China to the UK and Germany (0.01%). It is noticeable as well that the volatility transmission from the Chinese tourism stock market to other markets is negligible, which is due to the weak correlation between China's stock markets and other markets (Wang et al., 2022).

Table 3: Fall sample result of Diebold and Yilmaz's (2012) test

Volatility Spillovers (DY12)						
	Germany	UK	Turkiye	China	Italy	From
Germany	70.45	18.69	4.99	0.01	5.87	5.91
UK	5.44	31.42	19.56	0.01	43.58	13.72
Turkiye	0.27	9.24	89.45	0.19	0.84	2.11
China	0.07	7.32	1.33	89.20	2.09	2.16
Italy	0.40	5.31	2.06	0.03	92.20	1.56
TO	1.24	8.11	5.59	0.05	10.47	**Total volatility index= 25.46%**
Net	-4.675360	-5.604264	3.477178	-2.113590	8.916035	

Germany transmits the highest volatility spillovers to the UK and Italy, with 5.44% and 0.40%, respectively. Simultaneously, the UK transmits the most volatility spillovers to Germany. Moreover, Turkiye transmits the highest volatility spillovers to the UK and Germany, with 19.56% and 4.99%, respectively. On the other hand, all the tourism stock indexes receive the highest volatility spillovers from the UK and the least from China. Germany receives the largest volatility spillovers (18.69%), while Italy receives the least (5.31%).

To summarize, Germany, the UK, and China have received more spillovers from other markets than they have transmitted; thus, they have become net spillover recipients. Others are net spillover senders. Some of our findings are consistent with those of Li (2021), who studied the volatility spillover across global stock markets during COVID-19. He found that the Chinese stock market is a volatility spillover receiver, while Italy is a volatility spillover transmitter. Zhang et al. (2020) concluded that the UK stock market is a volatility spillover receiver. Finally, Coskun and Taspinar (2022) found that the Turkish energy stocks are volatility transmitters. They attributed this

result to the fact that the energy stocks in Turkiye may exhibit the same characteristics as the world's largest energy firms. Thus, the same theory can be followed with the tourism stocks, as Turkiye is a very famous international tourism destination.

4.2.2 Dynamic Analysis

This section investigates five markets' total and net directional spillovers during the pandemic. A 200-day rolling windows is used to estimate the dynamic volatility spillover effects. Figure 6 shows the time-varying total spillover index. The pre-COVID-19 period is between 0 and 1000, while the period after 1000 is the COVID-19 period. We can notice from the graphs that the most significant volatility exists in the COVID-19 period. Bouri et al. (2021) indicate that a global decline in real activity was experienced as a result of the impact of the COVID-19 pandemic, resulting in substantial volatility spillovers across markets. Moreover, Figure 7 presents each tourism stock index's time-varying net directional spillover index. Germany, the UK, and China have received more spillovers from other markets than they have transmitted; thus, they have become net spillover recipients. Others are net spillover senders.

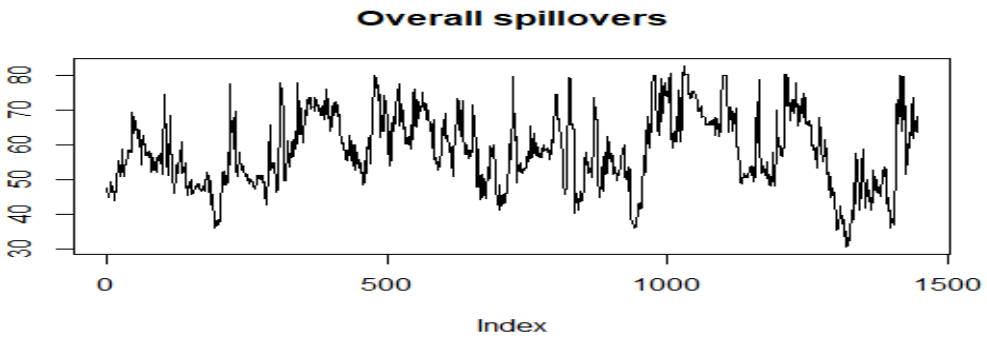

Figure 6: Time-varying Total spillover index

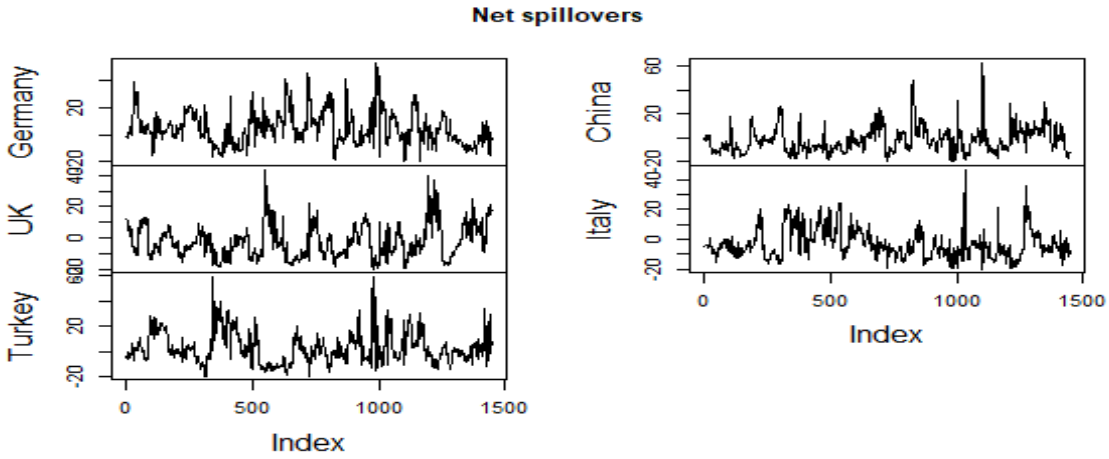

Figure 7: Time-varying Net directional spillover index

4.3 Barunik and Krehlik (2018) Results

Barunik and Krehlik's (2018) methodology is pursued, where the spillover table is decomposed into three distinct frequency groups by applying the Fourier transform. "Freq S" roughly corresponds to 1 day to 4 days (short-term frequency), "Freq M" nearly matches 4 days to 10 days (medium-term frequency), and "Freq L" nearly matches 10 days to infinity (long-term frequency). The figures in each column, labeled “FROM_ABS”, represent the percentages of volatility spillover that have been received from other markets, including its own; while “FROM_WTH” represent the percentages of volatility spillover that have been received from other markets, excluding its own. Moreover, the figures in each row, labeled “TO_ABS” and “TO_WTH”, show the percentages of volatility spillover that have been transmitted from one market to other markets, including and excluding its own, respectively.

Table 4 presents the spillover results of the three frequency groups of the Barunik and Krehlik (2018) test. We can observe that the total volatility spillover in the short-term frequency is the highest at 43.16%, followed by the medium- and long-term with

42.81% and 23.76%, respectively. This implies that the volatility spillover effect received from any market has a short duration.

Table 4: Results of Barunik and Krehlik's (2018) test.

Model Spillover Results (BK18)							
Frequency S 1–4 Days							
	Germany	UK	Turkiye	China	Italy	FROM_ABS	FROM_WTH
Germany	0.06	0.12	0.02	0.00	0.00	0.03	12.33
UK	0.13	0.56	0.05	0.00	0.01	0.04	16.47
Turkiye	0.01	0.05	0.02	0.00	0.00	0.01	6.30
China	0.01	0.03	0.01	0.00	0.00	0.01	3.89
Italy	0.01	0.03	0.01	0.00	0.00	0.01	4.16
TO_ABS	0.03	0.05	0.02	0.00	0.00	0.10	
TO_WTH	14.17	20.52	7.45	0.29	0.72		**43.16**
Frequency M 4–10 Days							
	Germany	UK	Turkiye	China	Italy	FROM_ABS	FROM_WTH
Germany	0.06	0.25	0.02	0.00	0.00	0.05	11.37
UK	0.29	1.27	0.07	0.00	0.00	0.07	15.54
Turkiye	0.03	0.12	0.01	0.00	0.00	0.03	6.31
China	0.02	0.08	0.01	0.00	0.00	0.02	4.62
Italy	0.02	0.09	0.01	0.00	0.00	0.02	4.96
TO_ABS	0.07	0.11	0.02	0.00	0.00	0.20	
TO_WTH	15.08	23.05	4.47	0.01	0.01		**42.81**
Frequency L 10-infinite Days							
	Germany	UK	Turkiye	China	Italy	FROM_ABS	FROM_WTH
Germany	73.56	2.87	8.20	0.08	14.76	5.18	5.22
UK	3.66	31.90	21.28	0.27	40.51	13.14	13.24
Turkiye	0.51	2.49	95.25	1.21	0.29	0.90	0.91
China	0.53	3.06	2.30	93.29	0.66	1.31	1.32
Italy	3.62	5.97	5.23	0.48	84.53	3.06	3.08
TO_ABS	1.67	2.88	7.40	0.41	11.24	23.60	
TO_WTH	1.68	2.90	7.45	0.41	11.32		**23.76**

Chapter 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

First, volatility spillover is considered one of the most highly investigated topics in the finance literature, as it is associated with risk transmission between stock markets and portfolio management. Second, the tourism sector has gained a lot of investors' and researchers' attention in the past two decades. Thus, this thesis examined the dynamics of volatility spillovers among five tourism stock indices during the COVID-19 period. Daily data have been extracted from Thomson Reuter's Data Stream for the period between September 2015 and January 2022. The five covered countries in this study are as follows: Germany, the UK, Turkiye, China, and Italy. These five countries were listed among the top 10 tourism destinations in 2020, according to the World Tourism Organization (UNWTO).

The aim of this study is to understand whether volatility is transmitted among the global tourism stock markets, and whether the effect of volatility transmission is temporary or persistent (long-lasting) for portfolio diversification purposes. Thus, this study employs Diebold and Yilmaz's (2012) connectedness methodology and Barunik and Krehlik's (2018) time-frequency methodology. Results suggest that total spillovers of the tourism stock indices rose significantly during the pandemic, reaching a historical level and experiencing some fluctuations since then. That is not in line with COVID-19's trend. This may result from the government's short-term monetary and

physical policies. Turkiye and Italy are net volatility spillover transmitters, while the others are net volatility spillover receivers. Moreover, the total volatility spillover in the short-term frequency is the highest, which means that financial markets are efficient and analyze the information quickly and act based on that.

5.2 Recommendations

The results of this thesis may have some important suggestions for investors. As short-term overall volatility spillover is the greatest, short-term investors and portfolio managers might not be able to find an interesting diversification opportunity. Thus, they should avoid the tourism stock indices in the short term. However, long-term investors and portfolio managers may profit from extensive hedging and diversification possibilities by including tourism stock indices in their portfolios.

Tourism conglomerates should take volatility connectedness of global tourism indices into consideration while creating short-term policies around financial stability. Uncertainties due to external shocks will affect the volatility of the tourism sector. Thus, the financial stability of tourism companies. Policymakers in the sector should focus not only on domestic risks and uncertainties, but also on global tourism economies. Policymakers should always follow net volatility transmitter countries to avoid short-term losses by taking precautions against volatility from others.

5.3 Study Limitations

COVID-19 has not reached its end yet. Thus, future studies may include expanded data. Moreover, our findings can be examined to determine if they are valid for the sub-sector indexes, such as airlines, restaurants, hotels, and gambling. Lastly, researchers may investigate the volatility spillovers among the tourism stock indexes in developed and developing countries for comparison purposes.

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