Assessing Sectoral Connectedness: The Case of the Financial Sector

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Abstract

This paper aims to measures connectedness and volatility spillovers between the main financial market sectors in the US and Europe. This study looks at different aspects of connectedness, from pairwise to system wide, as well as measuring directional connectedness. This is done in order to understand the dynamic nature of connectedness within sectors to assess trends or patterns during times of volatility and times of tranquillity. The methodology adopted here is from the framework developed by Diebold and Yilmaz (2011), whereby daily stock data from the sample sectoral ETFs is utilised from the period of November 2006 to March 2024. Such timeframe captures the effects of the Global Financial Crisis in 2008 and the Covid-19 Pandemic in 2020. Such findings suggest that there is an element of connectedness between sectors throughout the whole period and increases during times of financial crises. Furthermore, the results show that cyclical sectors tend to have higher levels of pairwise connectedness and also tend to be either net transmitters or receivers of volatility within the system.

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Table of Contents

List of Tables

List of Figures

Chapter 1 – Introduction, Objectives, Expectations and Hypotheses

The economy is subject to financial crises, which although do not happen frequently, tend to occur every decade or so. The financial crises that have occurred over the past decades tend to exhibit similarities. More specifically financial crises bring with them an increase in volatility and increased spillover effects from one sector to another. Furthermore, volatility does not tend to appear in isolation but in volatility clusters. Past crises have thought us that it is not just one sector or asset class that suffers from negative performance, but such shocks and negative performance in one sector or asset class extends into other sectors and assets classes. Thus, the study of connectedness is a crucial element in understanding how financial markets behave during times of financial distress.

The different financial sectors have emerged over time and can be divided into the nine most common categories, being technology, energy, health care, materials, financials, industrials, communications, utilities and consumer stables. These sectors have grown in both size and from a liquidity point of view. It is said that correlation between these sectors increases during times of financial distress, and therefore it is important to understand how shocks in one sector affects shocks in other sectors.

When Lehmann Brothers collapsed towards the end of 2008, shocks were transmitted throughout all the different sectors and affected the whole financial system. This crisis shed light on the danger of high connectedness between the different sectors, as it showed how shocks originating in one sector not only affects that sector but extends to other sectors. Connectedness therefore helps in understanding the potential repercussions that periods of financial stress and high volatility have on financial markets. From a risk measurement and management point of view, connectedness may be particularly useful.

This study focuses on the relationships between sectors and their connectedness levels, on both pairwise to system wide levels. One cannot mention connectedness without mentioning volatility spillovers since the two are closely related. Therefore, particular attention is given to volatility spillovers, which looks into how the shocks in one sector affect the shocks in another sector and the system as a whole. It looks into capturing and quantifying these particular relationships and ultimately understand the level of impact that may result in times of difficulty. This study builds upon the existing connectedness literature established by Diebold and Yilmaz (2011).

1.1 Scope of this Study

The aim of this paper is to understand financial connectedness between the different financial industries within the US and European financial markets. The methodology applied throughout this study is a connectedness measure developed by Diebold and Yilmaz (2011). The scope here is to measure connectedness at different levels, including pairwise connectedness as well as system-wide connectedness. Pairwise connectedness looks at the directional point of view, the 'To' and 'From' connectedness that a particular industry has, while the system wide aspect looks at the overall connectedness levels within the selected sectoral indices.

The chosen time frame is further divided into three sub samples. The first data set looks at the whole period between 2006 and 2023 in order to capture connectedness throughout the whole sample period. The second data set covers the period between 2008 and 2012, in order to include the effects of the global financial crisis as well as the European sovereign debt crisis. The third time period ranges from the beginning of 2020 up to the beginning of 2023 in order to assess the impact that the Covid-19 pandemic had on financial industries. The aim here is to provide insight into the various relationships between the different sectors within financial markets, the level of connectedness between sectors and to analyse any changes in such connectedness levels between the two different periods of economic distress.

1.2 Research Objective

The main objective of this study is to analyse and assess the connectedness level between the major different sectors within developed markets and to understand which sectors are more vulnerable during times of distress. The sample looks at the nine different sectors in the US and Europe during the timeframe from 2006 up to 2023. This research paper aims to study the connectedness levels between the different sectors during this timeframe. The method employed builds on the studies developed by Diebold and Yilmaz in 2011, which primarily focuses on US based firms.

This study also aims to analyse any patterns in connectedness during times of financial crisis and which sectors are more subject to volatility and how these shocks affect other sectors, in order to analyse which sectors have the highest levels of connectedness. This approach aims to identify any trends and how connectedness increases between the different sectors.

The main research objectives aim to focus on:

1. Understanding the overall connectedness levels between the different sectors and to see whether these findings are in line with past literature.
2. Identify pairwise connectedness between the different sectors and identify possible reasons for such findings.
3. Identify which sectors are net transmitters and net receivers of volatility.
4. Analyse the dynamic connectedness during the whole data set and the connectedness based in each region, being the US and Europe.

5. Analyse the levels of connectedness during the different time periods of financial distress, and to see if there are any similarities in the connectedness levels between the two crises.

1.3 Expectations

Some a priori expectations before conducting the study were formed, them being; that volatility spillovers increased during times of distress and that pairwise connectedness levels increased during times of distress. Another expectation is that during the financial crisis, the financial sector had a high level of spillovers, i.e. gave off the most shocks to other sectors, since banks were hit first. While during the Covid-19 crisis, it is to be expected that the industrials sector gave off the most shocks to other sectors, since the industrials sector was negatively impacted and very volatile.

1.4 Outline of the Paper

This paper is further divided into another five chapters. Chapter two presents the literature reviews, which look into past studies on connectedness and volatility within financial markets. This chapter also looks at the different methodologies employed, paying particular interest in the framework developed by Diebold and Yilmaz. This third chapter then takes a deeper look into the methodology used to conduct this study which follows the methods developed by Diebold and Yilmaz, in order to analyse connectedness between different sectors. The fourth chapter provides a description of the dataset used as well as the descriptive statistics and the necessary stationarity checks. The fifth chapter displays the implementation of the methodology and the analysis of the empirical results achieved. Lastly, the sixth chapter finalises this paper by presenting the overall conclusion, policy recommendations and avenues for future studies.

Chapter 2 – Literature Review

2.1 Introduction

Throughout the past decade or so, financial connectedness has been a keen topic of interest in the financial sphere. Interest in this field particularly arose due to the global financial crisis of 2007 to 2009 and following that the sovereign debt crisis in Europe. Researchers and academics such as Diebold and Yilmaz (2009), Degryse *et al.* (2010) and Paltalidis *et al.* (2015) have all published papers and academic journals in order to investigate the dynamics of connectedness.

Connectedness is mostly used to analyse the shock between the variables into the system and measure the relationship between the variables, and to determine how these variables affect each other through their shocks into the system. It mainly serves as a risk management function to measure market risk, credit risk and business cycle risk. When mentioning connectedness, one would first need to understand the concept of contagion and volatility spillovers. These two terms go hand in hand with financial connectedness. This chapter shall outline and discuss past literature on the topic, while giving particular interest on the academic studies and papers published by Diebold and Yilmaz throughout the past years. Their methodology applies a variance decomposition approach, which calculates volatility spillovers within a particular times series, which is mainly done by taking the returns of stock prices.

2.2 Contagion as a Transmission of Mechanism of Shocks

In order to understand connectedness one first needs to understand the concept of contagion in financial markets. Contagion is the term used to describe how shocks move across variables, for instance across markets, sectors, countries or regions, which may be direct or indirect. Contagion can be seen as the correlation between market excess that results from economic fundamentals, as explained by Bekaert *et al.* (2005). A contagion effect can also refer to a situation where financial asset movement increases at a specific moment resulting from a period of distress, which Forbes and Rigobon (2002) have outlined. This can also be applied to countries or regions, which Dungey *et al.* (2005) look into in their paper, where they argue that a contagious transmission explains how local shocks in a particular country of that asset, transmits into other markets or countries, in other words spillovers. Khallouli and Sandretto (2012) demonstrate how contagion can explain how shocks spread throughout variables due to herding behaviour and panic movements. In order for contagion to take place, there needs to be a high level of spillover effects (Alter and Beyer, 2014).

Contagion tends to result from either the behaviour of investors or from fundamental based reasons, according to Dornbusch *et al.* (2000). After the market crash of 1987, the topic on contagion especially in equity markets gained particular interest. King and Wadhwani (1990) studied contagion and found it was present in equity markets, which was done by analysing correlation in markets in the US, UK and Japan. They found that contagion arises due to investors that are rational and apply the information they gathered from other markets and interpret it to their own market. However, a contradictory study conducted by Forbes and Rigobon (2002), found that during the US crash of 1987 there was no evidence of contagion. Yilmaz, K. (2010) focused his study on East Asian Equity Markets where he examined contagion and interdependence across Asian equities since the early 1990s and compared it with the financial crisis. It was concluded that contagion increases in "bursts during major market crises, including the East Asian crisis". A recent study was conducted by Goutte, Guesmi and Uorm (2022) on financial contagion due to the Covid-19 pandemic, where they found that the pandemic had the biggest effect in co-movements between the energy commodity market and the stock market. Contagion running from Gold spot price to US market was higher than from the Chinese and European stock market.

2.3 Volatility Spillovers

Volatility has been a popular topic of research throughout the past few decades, especially when it comes to measuring and trying to forecast volatility within financial markets. Volatility can be seen as the measure of variation in a particular assets' price over time. In finance, volatility is used as a measure of risk, where the higher the volatility of an asset or market, the riskier that asset or market is said to be. This is because the asset is subject to greater fluctuations since it experiences higher or sharper changes in its price. Volatility tends to increase during periods of uncertainty or distress. An important feature of volatility is volatility clustering, which was first noted by Mandelbrot (1963) in his academic paper. He explained that volatility clustering is a situation where volatility appears in bunches and tends to follow a pattern whereby "large changes tend to be followed by large changes, of either sign, and small changes are tend to be followed by small changes."

Diebold and Yilmaz are considered to be the grandfathers of financial connectedness due to their extensive research on the subject. However, before starting their studies on connectedness, they had previously published many papers on volatility spillovers, more specifically the directional measurement of such spillovers. The first paper they published was in 2009, where they analysed global equity returns and volatility spillovers between the period of the early 1990s up to 2009. Volatility spillover is defined as the transmission of instability from asset to asset, sector to sector or market to market. Their methodology was based on vector autoregressive (VAR) models, by focusing on variance decompositions, which allowed them to "aggregate spillover effects across markets, distilling a wealth of information into a single spillover measure" (Diebold and Yilmaz, 2009). In this paper, they introduced a spillover index, which is a quantitative measure of interdependence, and also introduced what they call "spillover tables and spillover plots". They found that "return spillovers display a gently increasing trend but no bursts, whereas volatility spillovers display no trend but clear bursts".

In 2011 and 2012 Diebold and Yilmaz applied the same methodology to carry out another two studies. In 2011 they published a paper, which focused on equity market spillovers in Brazil, Argentina, Chile, Brazil, Mexico and the US. Their findings show that return and volatility spillovers were present within these countries. However, they found that when it comes to return spillovers, these evolve gradually whereas volatility spillovers occur in bursts in response to economic events, which further supports their previous findings. The 2012 study is also in line with their previous findings. Here they applied a further step to their previous methodology, that is of an autoregressive framework, where they introduce “forecast-error variance decompositions are invariant to variable ordering”. This method was used to measure total and directional volatility spillovers across equities, fixed income, commodities and foreign exchange markets in the US, from 1999 to 2009. They found that volatility fluctuations were present throughout the four different markets, however cross-market volatility spillovers only arose during the global financial crisis of 2007 and seemed to intensify as the crisis intensified. In particular, the fixed income market suffered from the highest volatility spillovers.

Adopting their methodology, Mile Ivanov (2014) examined the return and volatility spillovers in European markets between 2005 to 2014, by applying a multivariate GARCH-BEKK model and creating spillover indices. It was concluded that, “total spillover index rose sharply during the periods of major financial disruptions”. Furthermore, the study showed that the DAX and FTSE100 are the major transmitters of spillovers within European Markets. This could be attributed to these indices being the biggest markets in Europe. A more recent study conducted by Corbet, Hou and *et al*. (2020) on volatility spillovers during the Covid-19 pandemic. They found that the pandemic influenced financial markets as volatility increased, most notably that the pandemic affected the price of Bitcoin which resulted from directional volatility spillovers.

2.4 Understanding Financial Connectedness

This papers primary objective focuses on financial connectedness between the major sectors within US markets and European markets. As previously mentioned, understanding connectedness within financial markets is a key element when it comes to risk measurement and management. This is because connectedness is a key feature of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counterparty and gridlock risk (bilateral and multilateral contractual connectedness), and systemic risk (system-wide connectedness) which is explained by Diebold and Yilmaz (2014). It can also be used when it comes to macroeconomic risks, for example business cycle risk as it helps to understand underlying fundamentals. Connectedness may seem similar to correlation, however connectedness takes a deeper look into the variables. Correlation only gives information on pairwise associations and is simply linear and gives no information on the direction of the relationship between the two variables. Connectedness gives information on how the shocks within one variable or how the shocks around one variable affects another variable, or how those shocks affect the system as a whole.

Connectedness can be applied to a wide range of variables in order to examine different topics. For instance, it can be applied on a cross-firm, cross-asset, cross-market, cross-country level, regarding various assets, asset classes, portfolios, and other entities. Furthermore, the degree to which financial markets are interconnected is more closely correlated with the volatility spillover or contagion, which has gained attention after the global financial crisis of 2008. (Billio *et al.,* 2012). Connectedness gives insight into financial stress co-movements and risk transmission across financial assets, sectors and markets. This is why contagion and connectedness gained particular attention after the Global Financial Crisis of 2008, because this crisis showed how a relatively small crisis in the US housing market triggered a financial crisis that not only spread throughout the US but throughout the rest of the world. Past literature on this topic all conclude with a common consensus, that financial contagion and connectedness among international markets increase during periods of economic and financial stress as markets have become more integrated and interconnected (Balcilar, Elsayed, Hammoudeh, 2023).

2.5 Studies Performed by the Authors

Diebold and Yilmaz applied their studies and methodology that they used to study volatility spillovers to create and then adopt a unified model for conceptualizing and measuring connectedness at different levels. Their research on connectedness included both pairwise connectedness (relationship between two variables) as well as system-wide connectedness. The VAR models that they had previously used to measure volatility spillovers was applied, were they used variance decompositions from approximating models. This measure has been adopted and has been extended numerous times by many academics and researchers, since it has been proven to be a very accurate measure of connectedness and is not too complex to implement.

In their 2014 paper, Diebold and Yilmaz introduced several connectedness measures, which included population connectedness which is an “approach to connectedness is based on assessing shares of forecast error variation in various locations (firms, markets, countries, etc.) due to shocks arising elsewhere”. Here they tracked daily time varying connectedness of major US financial institutions by focusing on their stock return volatility, giving particular importance to data during the financial crisis between 2007 and 2008. In their study, connectedness is used in the context of shares, where shares are assessed on the basis of forecast error variation in different locations, such as firms, markets, countries and regions due to shocks arising somewhere else. The variance decomposition shows how much information each variable contributes to the other variables in their regression. It demonstrates how much the forecast error variance of each variable is explained by exogenous shocks to the other variables. Furthermore, the same method they had previously used to create the spillover table, was used to create the connectedness table, which provides information on the connectedness relationships between the variables in the system.

The above methodology can also be applied to examine business cycle connectedness. In their 2015 paper, Diebold and Yilmaz show that "global connectedness is sizable and varies over the business cycle". They also found that when shocks within one country are small, those shocks remain contained within that country, however when shocks are of a substantial size they are transmitted and "the cross-country correlation of macroeconomic aggregates increases". They also found that between the 1970s to the 2000s, the US and Japan were the major net transmitters of shocks to other countries, and Germany was the major net receiver of such shocks.

In 2016, Diebold and Yilmaz used the same methodology however this was applied to volatility connectedness between US and European financial institutions. This was done by taking the daily equity returns between 2004 to 2014. Their paper outlined that during at the beginning of the financial crisis period connectedness was mainly coming from the US to the EU. However, as the crisis progressed "that connectedness became bi-directional", meaning that the two markets became a source of connectedness to each other. Later on in 2011, as the financial crisis spilled over into the EU and the European Sovereign debt crisis started to emerge, directional connectedness shifted from European to US financial institutions, as European financial institutions were emanating shocks and transferring volatility onto the Bank of New York and American Express Bank. More specifically, Spain, Italian, French and British institutions were transmitting shocks to other financial institutions.

Bostanci and Yilmaz (2020) published a paper on connectedness on sovereign credit default swaps (SCDSs) in order to determine the level of connectedness between sovereigns, giving particular importance to the financial crisis. They found that connectedness was considerably high and the behaviour of connectedness between sovereigns was similar to connectedness between stock and FX markets. Furthermore, developed markets transmitted less sovereign credit risk as compared to emerging countries, such as Russia, Turkey and Latin America. In 2018 Korobilis and Yilmaz estimated a large VAR model by utilizing daily stock return volatilities of thirty-five US and European financial institutions, however using a slightly different approach than used by Diebold and Yilmaz. The TVP-VAR model connectedness index did not display excessive persistence, however there are more pronounced jumps during times of crises and therefore captures tension within financial markets more accurately. They found that the TVP-VAR model is a better measure of systemic risk rather than the rolling-window based connectedness index which Diebold and Yilmaz had previously used.

2.6 Studies Utilising the Diebold and Yilmaz Methodology

Studies utilizing the Diebold and Yilmaz methodology on connectedness have been applied throughout different countries and different types of markets. Balcilar, Elsayed and Hammoudeh (2023) recently conducted a study on the financial connectedness and the transmission of risk among the Middle East and North Africa (MENA) countries, by calculating pairwise directional and net directional connectedness. Through their study they found that the five Gulf countries are highly connected between themselves as compared with other countries, while Tunisia has the lowest level of connectedness with the other MENA countries. They also found that “Saudi Arabia is the prevalent net financial stress risk transmitter, while Bahrain, Jordan, Qatar, and Oman are significant receivers”, whereas the Gulf countries are both net receivers and net transmitters.

Costa, Matos and Silva (2020) carried out a study on sectoral connectedness within US markets, focusing on the effects that the Covid-19 pandemic had. This was done by applying the Diebold and Yilmaz method, using daily data from eleven US sectoral indices. As expected, they found an increase in volatility connectedness and network connectedness during the pandemic, which lasted from the early stages of the pandemic up to the end of the pandemic. Each index experienced an increase in volatility spillovers from the system, and also experienced an increase on how much volatility spillovers they gave off to the system. There were also changes in pairwise relationships, however “most indices have maintained their status as net senders/receivers of connectedness to the system during the pandemic as compared to the previous tranquil period”. Furthermore, the sector that had the highest daily value of connectedness to the system was the Energy sector, and the Financials sector showed to be a “relevant sender of connectedness during the pandemic”.

A study comparing sectoral connectedness between the financial crisis and the Covid-19 Pandemic was carried out by Laborda and Olmo (2021). This was done by utilizing the Diebold and Yilmaz methodology were they measured volatility spillovers between seven sectors of economic activity. They found that the sectors which mainly transmit shocks to the economy are; Energy, Biotechnology, Technology and Banking and Insurance. More specifically, the Banking and Insurance sector was the main transmitter during the financial crisis, whereas the Energy sector was the main transmitter during the Covid-19 crisis. The net receivers of such shocks were found to be the Pharmaceuticals sector and the Health care sector. In line with previous studies, volatility spillovers were found to have increased during times of distress and crises. Interestingly, they found that the Biotechnology sector was the exception.

In 2022, Mensi, Rababa and et al submitted a paper on the volatility spillovers and connectedness between commodity and stock markets. It was concluded that utilities, financials, consumer staples, health care, communication services, gold futures and crude oil futures are net receivers of spillover in the system”, while the other sectors are net contributors. From a risk management point of view, when oil and gold assets are added to a sector portfolio, the extent of spillovers reduces, this is because “spillover from commodities to the sectoral markets is less from gold relative to that from oil”. As noted in previous studies, the connectedness levels amongst markets depends on market conditions and tends to be heterogenous. For instance, connectedness between the energy sector and crude oil market is high, while the connectedness levels from consumer staples and services to gold and crude oil is low. Furthermore, they noted that oil can be used as an effective hedging tool even during times of crises and volatility and tends to be more effective in the long term rather than the short term. Another interesting study on the effects of the pandemic was carried out by Imran, Saba and *et al.* (2023), where they studied the effects of the vaccine on connectedness. They found strong connectedness levels between the vaccine with financials, industrial, health care, information technology, communications services and real estate sectors, whilst finding a low level of connectedness with the utilities sector and IT services. Overall, the Covid-19 vaccination helped in the recovery of the performance of sectoral equity indices.

2.7 Conclusion to the Literature Review

The literature review provided an explanation into the main concepts of financial connectedness, such as contagion and volatility spillovers. This chapter also provided an overview of the measures and models available for measuring connectedness. Furthermore, we have seen how connectedness can be used as a measure of risk when it comes to portfolio management. Past literature shows that connectedness between variables increases during times of uncertainty and distress. Furthermore, the US and Europe also seem to export shocks to one another and institutions that are larger tend to be higher exporters of connectedness.

Chapter 3 – Methodology

3.1 Introduction

This chapter outlines a description of the research approach, as well as the methodological steps taken to try answer the research question. The approach taken follows the econometric model developed by Diebold and Yilmaz (2012), and shall focus on sectoral connectedness, which will be outlined further throughout this chapter. This approach aims to provide insight on contagion levels, by measuring connectedness levels on both pairwise relationships through system wide relationships. This means that the methodology examines the shocks between variables within the system at an individual level, and also at a system wide level as it examines connectedness of the whole system, meaning at an aggregate level. This chapter outlines and explains various outputs, connectedness relationships, the connectedness table and the difference between static and dynamic modes.

3.2 Research Approach and Data Collection Method

A quantitative research approach was used throughout this research paper, whereby secondary data was primarily used. When it comes to the method, such research was based upon existent literature, focusing mainly on the studies and methodology carried out by Diebold and Yilmaz throughout 2011 and 2014. The observations and results will be discussed towards the end of the study.

In order to carry out the below methodology, a substantial amount of data needed to be collected. The data collected was based on publicly available stock return data, more specifically the closing price of Exchange Traded Funds (ETFs), which was collected from Bloomberg. This study is based on daily data as opposed to intra-day values used by Diebold and Yilmaz throughout their studies. Further details on the selected period and data collected is outlined in the next chapter.

3.3 The Econometric Model

The approach taken here follows the Diebold and Yilmaz (2012) framework, in order to analyse the connectedness levels between different industries with US and EU markets. This framework measures the level of connectedness at different levels, "from pairwise through system-wide" *Diebold and Yilmaz (2011).* This is achieved by approximating models via variance decompositions which are approximated through the use of Vector Autoregressive Models.

Through their research papers, Diebold and Yilmaz apply the Variance Decomposition model in order to explain how changes in "other variables can explain much of the H-step-ahead forecast error variance of the given variable" (Diebold and Yilmaz, 2011). By applying this method to this study, the connectedness model applied is based on analysing share prices (from different industries) of forecast error variations in specific locations as a result of shocks arising in a different location.

The H-step variance decomposition component is denoted by $d_{i\,j}^{H}$. This comes from the notion of variance decomposition, where i which is the forecast error variance is decomposed into parts attributed to the different variables in the system. Therefore, $d_{i\,j}^{H}$ explains the fraction of variable i's H-step forecast error variance due to shocks in variable j. These connectedness measures, which range from pairwise to system wide are based on cross variance decompositions, denoted by $d_{i\,j}^{H}$, where $i, j = 1, \dots, N, i \neq j$. It is important to note that $i \neq j$, which is the key concept here.

3.4 The Connectedness Table

Diebold and Yilmaz created a connectedness table, in order to better explain the different connectedness measures and their relationships. The upper left of the table refers to the "variance decomposition matrix" which is denoted by $D^H = d^H_{i\,j}$. The rightmost column represents the row sums and the bottom row represents the column sums. The bottom right figure represents the grand average, which in all cases $i \neq j$.

	x_1	x_2	$\cdots$	x_N	From others
x_1	d^H_{11}	d^H_{12}	$\cdots$	d^H_{1N}	$\Sigma^N_{j=1} d^H_{1j}, j \neq 1$
x_2	d^H_{21}	d^H_{22}	$\cdots$	d^H_{2N}	$\Sigma^N_{j=1} d^H_{2j}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d^H_{N1}	d^H_{N2}	$\cdots$	d^H_{NN}	$\Sigma^N_{j=1} d^H_{Nj}, j \neq N$
To others	$\Sigma^N_{i=1} d^H_{i1}$ $i \neq 1$	$\Sigma^N_{i=1} d^H_{i2}$ $i \neq 2$	$\cdots$	$\Sigma^N_{i=1} d^H_{iN}$ $i \neq N$	$\frac{1}{N} \Sigma^N_{i,j=1} d^H_{ij}$ $i \neq j$

Table 4. 1 Diebold and Yilmaz Connectedness Table (Source: Journal of Econometrics 2014)

The diagonal entries of D^Hrepresent the shocks from their own connectedness. For example, the first input, shows its own connectedness. The off-diagonal entries of D^H (which are the parts of the N forecast error variance decompositions) represents pairwise directional connectedness, which represents the shocks originating from other variables. Therefore, pairwise directional connectedness from variable j to i is defined as:

$$C^H_{i \leftarrow j} = d^H_{ij}$$

It is important to note that generally, $C^H_{i \leftarrow j} \neq d^H_{i \leftarrow j}$, which means that there are $N^2 - N$ separate pairwise directional connectedness measures. Pairwise directional connectedness can be split into either "gross" or "net" connectedness. **Gross** pairwise directional connectedness can be shown by the summation of the off-diagonal elements, outlining the error variance of i as a result of shocks from the other variables. The Net directional connectedness is therefore defined as $C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H}$. Here there are $\frac{N^2 - N}{2}$ net pairwise directional connectedness measures, which represents bilateral trade balances.

Total directional connectedness can be seen in the rightmost column and the bottom row which are labelled 'from' and 'to'. The sum gives the portion of the H-Step forecast error variance of variable 1 coming from shocks arising in other variables. Total directional connectedness **from** *others* to i can be defined as:

$$C_{i\leftarrow \cdot}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{H}$$

Furthermore, directional connectedness **to** others from variable *j* can be defined as:

$$C_{\cdot\leftarrow i}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{H}$$

There are $2N$ total directional measures of connectedness, one being the N *transmitted* to others and the other N being *received* from others. Net total directional connectedness sums up to N, therefore we can define net total directional connectedness for i as:

$$C_{i}^{H} = C_{\cdot\leftarrow i}^{H} - C_{i\leftarrow \cdot}^{H}$$

This shows whether a particular variable contributes more to the system variation than the system variations to i. If the result is larger than zero, this means that the variable i is an exporter of volatility, meaning that the variable exports more volatility into the system than it receives.

Therefore, a result less than zero means that the variable is an importer of volatility, meaning it receives more volatility than it gives off.

The last element in the connectedness table left to describe is the off diagonal entries in D^H. This is the total sum of the 'from' column or 'to' row which measures the total connectedness in the system, which is expressed into a single number. Therefore, total connectedness can be defined as:

$$C^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} d_{i\,j}^{H}$$

The average of the sum of the "from others" others column and the average of the "to others" should be equal.

Diebold and Yilmaz created this connectedness table to aid in explaining a meaningful unified model for conceptualizing and measuring connectedness at different levels, including pairwise connectedness as well as system-wide connectedness. Throughout this study, this model is adopted in order to analyse how different industries may be connected to other industries or how one particular industry affects another ($C_{i\leftarrow j}^{H}$for various j). Furthermore, the study also aims to look into how all industries connect into a single one $C_{i\leftarrow\cdot\cdot}^{H}$

3.5 Correlated Shocks

Variance decompositions are easily calculated when it comes to an orthogonal reduced form system, however reduced form shocks are hardly ever orthogonal. Therefore, in order to distinguish between uncorrelated and correlated reduced form shocks, some assumptions need to be made. Thus, the model suggests either using the generalized variance decomposition (GVD) framework or the Cholesky factor autoregression. The variance decomposition results depend significantly on the order of the variables in the VAR. Therefore, due to this limitation, the

GVD framework is applied to this study since here the variance decompositions are not influenced by the order of the variables. Pesaran and Shin (1998) developed the GVD model, whereby the shocks may not necessarily be orthogonal and therefore not influenced by the order of the variables. However, this means that the sums of the forecast error variance contributions does not mean that it will be units (i.e. not equal to one). Due to this, the generalized connectedness index will be based on $\widetilde{D}^g = [\widetilde{D}^g_{ij}]$, where:

$$\tilde{d}^g_{ij} = \frac{d^g_{ij}}{\sum_{j=1}^{N} d^g_{ij}}.$$

Using $\widetilde{D}^g$, the generalized connectedness measures can be calculated straight away.

3.6 Rolling Sample Estimates

Diebold and Yilmaz (2009) created a measure to capture daily connectedness by applying a rolling window estimation. They created this measure in order to take into account the assumption that connectedness and spillover levels would change over time throughout the sample period. This method makes use of a "one-sided estimation window of width w, sweeping through the sample, at each period using only the most recent w periods to estimate the approximating model and calculate connectedness measures" (Diebold and Yilmaz, 2014). This can be written as: $\widehat{C}_t(x, H, M_{t-w:t}(\hat{\theta})$. The advantage of using this rolling-window approach is that it is coherent and simple to apply, whilst providing a wide range of underlying parameters. Another advantage is that this model provides more insight into the framework especially when it comes to the ability to time events and in turn analyse how these events affect connectedness. For this study a rolling estimation window of a two hundred days is used (w = 200 days), as well as a VAR (1) approximating model.

3.7 Relationship within the Network

Diebold and Yilmaz noted that their methodology goes hand in hand with modern network theory. A network is composed of 'N' nodes and 'L' links between nodes. $S_{i\,j}$ is the smallest distance between the two nodes 'i' and 'j' that must be travelled across in order to move the i^{th} to the j^{th}node. The $S_{i\,j}$ value does indeed represent the connectedness level, however it does not represent the strength of the connectedness relationship. Therefore, it is important to take into account the concept of node degree since it outlines the most important measures. The node degree (i) outlines the number of links to other nodes, which can be defines as:

$$\delta_i = \sum_{j=i}^{N} A_{i\,j} = \sum_{j=i}^{N} A_{i\,j}$$

Furthermore, the pattern of degrees across nodes can be examined, whereby the probability distribution of degrees across nodes is equal to the degree distribution. Here the degree of distribution is a discrete univariate distribution, which is closely related to the network behaviour i.e. connectedness. Therefore, here the location of the degree distribution is very important. The mean here is the standard location measure, which represents a measure for overall connectedness. This means that the larger a mean degree, then the higher the overall network connectedness.

3.8 Conclusion

This chapter outlines the methods adopted from the Diebold and Yilmaz framework. Such methods employed throughout this paper aim to provide an accurate and overall understanding of the level of connectedness between different industries within the US and EU markets, as well as how the levels of connectedness changed throughout periods of high volatility i.e. in times of a crisis. The methods and definitions outlined in this chapter provide an explanation into the model and the econometric nature behind the model.

Chapter 4 – Data Description and Analysis

4.1 Introduction

This chapter outlines the data selected in order to conduct this study and provides an analysis of the data selection process, as well as a statistical analysis of the dataset. The final results are then outlined in Chapter 5.

4.2 Data Categorization

The dataset used to carry out this study spans between 2006 up to the beginning of 2024. The dataset was divided into three samples;

1. Full sample; between 17^{th} of November 2006 up to 4^{th} March 2024;
2. Financial crisis period; 1^{st} of May 2008 up to 31^{st} December of 2012; and
3. COVID-19 period; 3^{rd} of February 2020 up to 5^{th} of May 2023.

The rationale behind using this wide time frame is to analyse the levels of connectedness between different sectors during times of distress, as well as to capture any similarities or trends in how different sectors behaved between the financial crisis and the Covid-19 pandemic. The timeframe for the financial period selected was between the beginning of 2008 up to 2012, since at the beginning of 2008 there were indications that the economy would collapse, and up until 2012 since the financial crisis then resulted in the European debt crisis in 2012. Furthermore, the timeframe for the Covid-19 pandemic was chosen, as during the second month of 2020 effects of Covid-19 started to spillover into other countries, and on the 5^{th} of May 2023 the World Health Organization declared the end of Covid-19.

In order to capture how the different sectors behaved during the selected timeframe, daily returns from different sectoral ETFs were used from the US and European markets. Sectoral ETFs were selected, in order to analyse the level of connectedness between sectors as well as spillovers from one sector to another. More specifically an ETF for each specific sector was chosen because ETFs most accurately represent how an industry behaves, since they replicate the performance of sectoral indices. Furthermore, the nine main industries from both the US and Europe were chosen in order to analyse the level of connectedness and volatility in the two major developed markets, as well as the level of spillovers from one sector to another, if any. The below table outlines the sectors as well as the selected ETFs;

	US Markets		**EU Markets**	
Sector	**ETF Name**	**Ticker**	**ETF Name**	**Ticker**
Technology (Tech)	Vanguard Information Technology Index Fund ETF Shares	VGT US	SPDR MSCI Europe Technology	STK FP
Energy (Enrgy)	Energy Select Sector SPDR Fund	XLE US	iShares STOXX Europe 600 Oil & Gas ETF	SXEPEX GY
Health Care (Hlth)	Health Care Select Sector SPDR Fund	XLV US	iShares STOXX Europe 600 Healthy Care ETF	SXDPEX GY
Materials (Mat)	VanEck Gold Miners ETF	GDX US	iShares STOXX Europe 600 Construction & Materials	SXOPEX GY
Financial (Finc)	Financial Select Sector SPDR Fund	XLF US	Amundi STOXX Europe 600 Banks	BNK FP
Industrials (Indus)	Industrial Select Sector SPDR Fund	XLI US	iShares STOXX Europe 600 Industrial Goods & Services	SXNPEX GY
Communications (Comm)	Vanguard Communication Services Index Fund ETF	VOX US	iShares STOXX Europe 600 Telecommunication	SXKPEX GY
Utilities (Util)	Utilities Select Sector SPDR Fun	XLU US	iShares STOXX Europe 600 Utilities	SX6PEX GY
Consumer Staples (Cnsm)	Consumer Staples Select Sector SPDR Fund	XLP US	iShares STOXX Europe 600 Food & Beverage	SX3PEX GY

Table 4.2: List of Sectoral Indices

As previously mentioned, such data was collected from Bloomberg, by using the ETF screen function which was used to search for ETFs. There was no need for currency conversion, since this study focuses on price volatilities within different industries.

The below figures represent the stock price changes from all the selected ETFs within the EU. Initially, in most of the ETFs, we can notice that there is a sharp price decline during the financial crisis, as well as during the European debt crisis and later on during Covid-19. From the below graphs we can see that during the financial crisis, the Financials Industry and Utilities industry suffered from the sharpest decline, whilst the Consumer industry suffered the least.

The below figures represent the stock price changes from the selected European Sectoral ETFs.

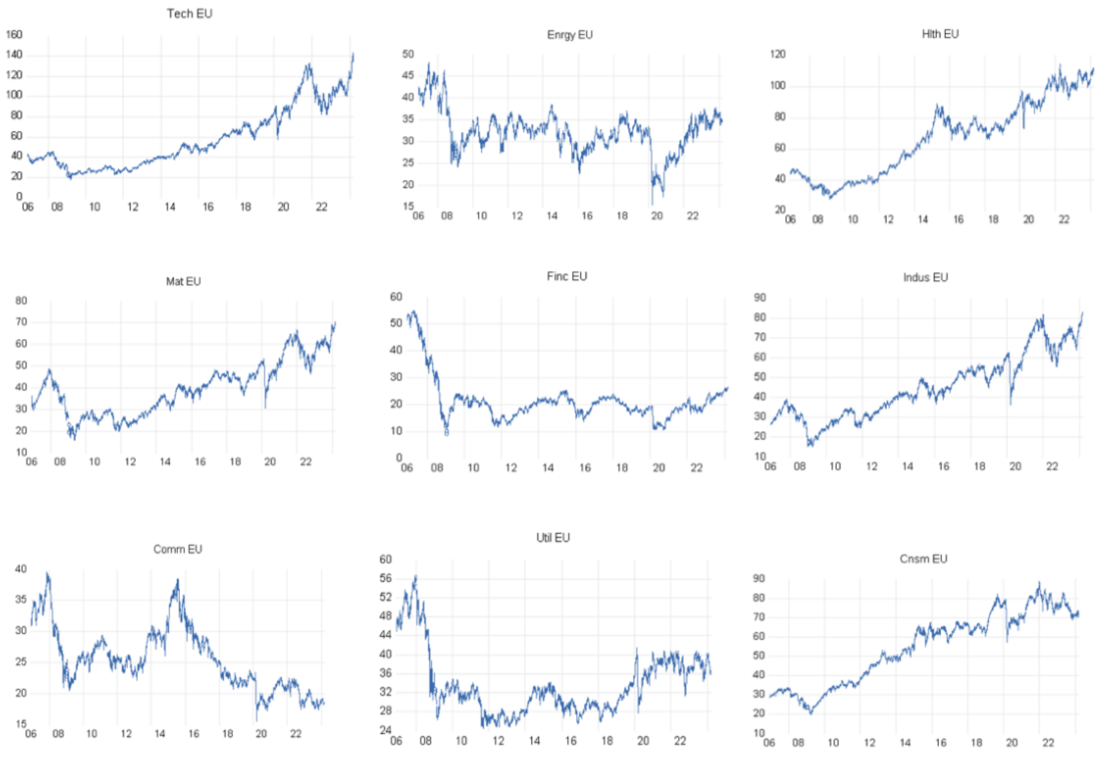

Figure 4.1 - European Sectoral ETF Returns

The below figures represent the stock price changes from the selected US Sectoral ETFs.

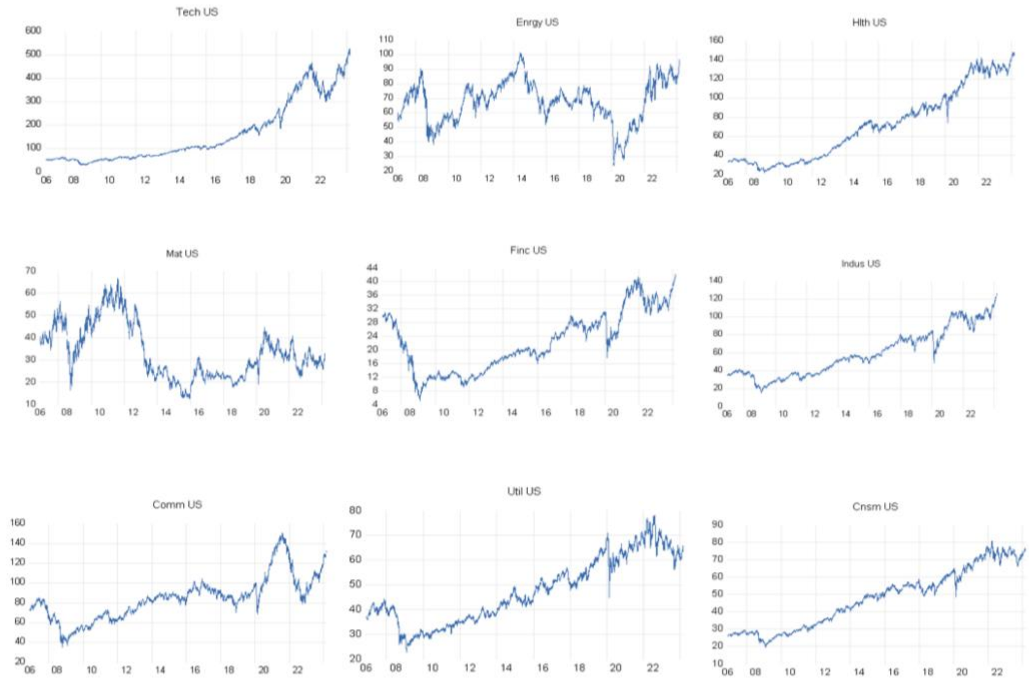

Figure 4. 2 - US Sectoral ETF Returns

Before proceeding to conduct the methodology developed by Diebold and Yilmaz, it is important to ensure that the data selected is stationary in order not to have spurious results. It is common knowledge that financial data is not stationary, and therefore logs were applied to the daily closing prices of the ETFs, which transposes the daily closing prices into the daily returns, and thus aiming to make the data stationary. This goes hand in hand with the methodology conducted by Diebold and Yilmaz since their studies focus on return volatilities. Log returns are computed from the closing prices of all the selected ETFs. Denoting PT as the value for the particular ETF at time t and Pt-1 at time t-1, the log return is computed by:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$$

The below figures represent the log-returns of the selected European ETFs. For all the sectors, one can note volatility clustering at different time periods. In particular, there is a spike in price volatility during the financial crisis in 2008. There is also another smaller spike during the European sovereign debt crisis in 2011, as well as another large spike during the Covid-19 pandemic in 2020.

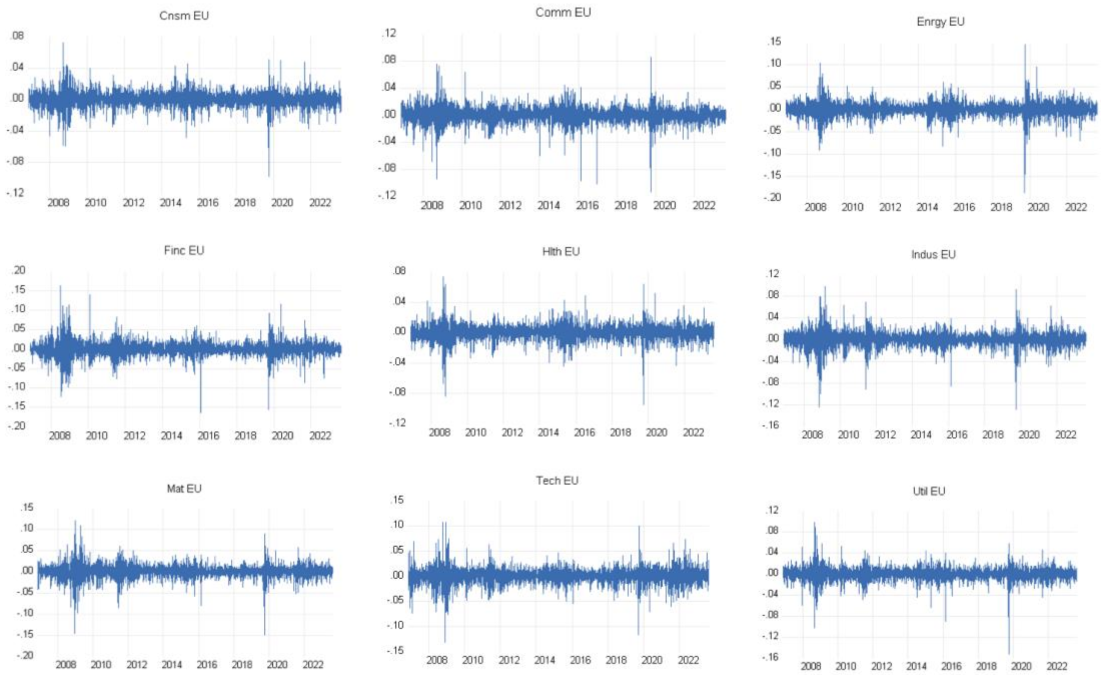

Figure 4. 3 - European Sectoral ETF Log Returns

The below figures represent the log returns for the selected US ETFs. The below graphs show the same volatility clustering at the same time periods. A priori expectations are that the European ETFs would have suffered from greater volatility clustering during the European Sovereign debt crisis in 2011, however it can be seen that the US ETFs also suffered from about the same level of volatility spikes.

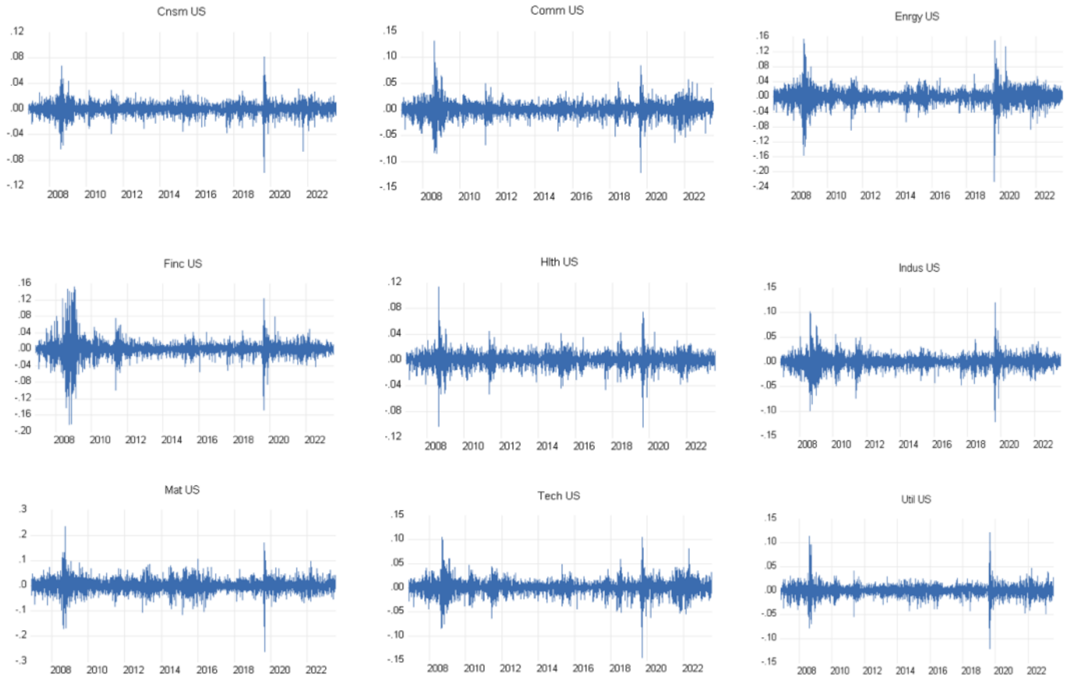

Figure 4. 4 - European Sectoral ETF Log Returns

4.3 Testing for Stationarity

As previously mentioned, it is very important to ensure that the data set is stationary, as a stationary data set is not subject to seasonal effects. Besides not wanting a spurious regression, connectedness looks at the shocks in the system, which means that if the data set is not stationary, the connectedness analysis will not provide accurate results.

In order to check that the data is stationary, once the data was transformed into log returns, unit roots tests were then carried out, mainly the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Philips-Schmidt-Shin (KPSS), which were carried out on all eighteen ETFs. Such results are outlined further below.

The below table outlines the results obtained from the ADF tests and the KPSS tests:

	ADF	KPSS
Tech US	-71.9123***	0.1934***
Enrgy US	-70.4179***	0.0601***
Hlth US	-71.7381***	0.1058***
Mat US	-50.0618***	0.0570***
Finc US	-74.1429***	0.3434***
Indus US	-69.6675***	0.0938***
Comm US	-69.6091***	0.0859***
Util US	-72.4420***	0.0510***
Cnsm US	-72.8315***	0.0436***
Tech EU	-67.4394***	0.2369***
Enrgy EU	-64.0612***	0.0455***
Hlth EU	-66.8318***	0.1044***
Mat EU	-65.0695***	0.1271***
Finc EU	-63.5145***	0.2825***
Indus EU	-64.5681***	0.0396***
Comm EU	-49.5580***	0.0434***
Util EU	-48.8279***	0.1284***
Cnsm EU	-67.3139***	0.1026***

Table 4.3 - Stationarity Tests

*Notes: For ADF *, **, *** signify rejection of the null hypothesis at the 10, 5 and 1% significance levels For the KPSS *, **, *** signify failure to reject the null hypothesis at the 10, 5 and 1% significance levels*

When looking at the ADF result, the results suggest that the data is indeed **stationary**, due to the following reasons. Firstly, from the table above, the ADF Test statistic result is greater than any of the critical test values, therefore the null hypothesis is rejected and thus the time series is stationary. Secondly, the null hypothesis is generally rejected when the p-value obtained is less than the 10% significance level. Therefore, in all eighteen cases, the p-value is zero, and therefore it is smaller than all significance levels. This means that the null hypothesis can be rejected at the 10,5 and 1% significance level. Since the null hypothesis is rejected, we can conclude that the data set is stationary.

When it comes to the KPSS test, one should reject the null hypothesis when the critical values are less than the test statistic, which implies that the data is non-stationary and unit root is present. In this case since all the values of the Test statistic are smaller than all the critical values, then the null hypothesis is not rejected, and therefore the data is stationary. Such results further support the ADF results, that is the data is stationary.

4.4 Descriptive Statistics

4.4.1 Descriptive Statistics for Whole Sample – US Sectors

Table 4.3 outlines the descriptive statistics for the daily prices of all the nine sectors within the US. Initially, it is noted that the Materials index has the highest standard deviation, followed by the Financials index and the Energy Index, which means that these industries displayed the highest levels of risk. Whereas the Consumers index has the smallest standard deviation, which is in line with our a priori expectation since the Consumers is a defensive sector, meaning it should have a lower level of risk as compared to other sectors that are not a defensive sector.

Full Sample 17/11/2006 - 04/03/2024 (4350 observations)									
	CNSM_US	COMM_US	ENRGY_US	FINC_US	HLTH_US	INDUS_US	MAT_US	UTIL_US	TECH_US
Mean	0.00024	0.00014	0.00011	0.00008	0.00034	0.00029	-0.00004	0.00013	0.00053
Median	0.0006	0.0007	0.0005	0.0005	0.0007	0.0009	-0.0003	0.0007	0.0012
Maximum	0.0817	0.1308	0.1525	0.1519	0.1138	0.1191	0.2354	0.1204	0.1045
Minimum	-0.0987	-0.1213	-0.2249	-0.1823	-0.1038	-0.1204	-0.2591	-0.1206	-0.1449
Std. Dev.	0.0093	0.0137	0.0197	0.0198	0.0110	0.0139	0.0261	0.0123	0.0146
Skewness	-0.4336	-0.2890	-0.7060	-0.1984	-0.3406	-0.4047	-0.1107	0.0240	-0.3380
Kurtosis	14.0909	11.2681	16.1229	17.5816	13.8578	11.7239	10.2595	16.9044	10.3793
Jarque-Bera	22431.55	12451.11	31574.58	38566.33	21452.15	13913.14	9560.84	35042.04	9952.54

Table 4.4 - Descriptive Statistics of US Sectoral ETFs (Full Sample)

The Jarque-Bera gives us information on normality. This can be defined as:

$$W = T\left[\frac{b_1^2}{6} + \frac{\langle b_2 - 3\rangle^2}{24}\right]$$

The null hypothesis here is that it assumes that the data set is normally distributed. Here, the Jarque-Bera Test for all industries have a P-value of 0, and therefore one can reject the null hypothesis of a normal distribution for all industries, which means that the sectoral indices do not follow a normal distribution. Such results contradict the results obtained from the skewness results which indicates that the data follows a normal distribution.

When taking a look at the skewness levels, one can note that all of the variables exhibit a negative skewness, except for the Utilities index. It can also be noted that all the variables are moderately skewed since the values are within the 1 and -1 range. However, it is important to note that the closer the value is to zero, then the closer the data is to following a normal distribution. The two sectors that are considered to suffer from the highest level of skewness is the Energy index and the Consumers index. When it comes to the kurtosis values, all the variables exhibit positive values and are leptokurtic, which means that they have heavier tails and are subject to outlier events. Although all variables have roughly the same kurtosis, the Financials index and the Utilities index, which suggests that these two industries suffered from the sharpest declines.

4.4.2 Descriptive Statistics for Different Time Periods – US Sectors

This study analyses the connectedness between different industries at different time periods, in particular distressed periods, and therefore we shall not only look at the descriptive statistics of the whole sample, but we shall also look at the descriptive statistics in the two distressed periods as well, in order to form some further a priori expectations.

The below tables display the descriptive statistics for the US market during periods of distress:

Financial Crisis Period 01/03/2008 - 31/12/2012 (1176 observations)	CNSM_US	COMM_US	ENRGY_US	FINC_US	HLTH_US	INDUS_US	MAT_US	UTIL_US	TECH_US
Mean	0.0002	0.0000	-0.0001	-0.0003	0.0002	0.0000	-0.0001	-0.0001	0.0002
Median	0.0008	0.0009	0.0004	0.0000	0.0006	0.0007	-0.0003	0.0003	0.0010
Maximum	0.0666	0.1308	0.1525	0.1519	0.1138	0.1017	0.2354	0.1140	0.1041
Minimum	-0.0621	-0.0844	-0.1560	-0.1823	-0.1029	-0.0988	-0.1688	-0.0773	-0.0833
Std. Dev.	0.0104	0.0167	0.0235	0.0301	0.0127	0.0180	0.0298	0.0137	0.0168
Skewness	-0.3289	0.0436	-0.4782	-0.0777	-0.2150	-0.1945	0.2113	0.6362	-0.1099
Kurtosis	8.3155	10.6034	12.1566	10.0571	14.9891	6.9009	10.4348	15.2393	7.4330
Jarque-Bera	1405.69	2833.12	4153.12	2441.50	7052.27	753.04	2717.29	7419.55	965.31

Table 4.5 - Descriptive Statistics of US Sectoral ETFs (Financial Crisis Period)

From the mean results it can be noted that most of the US sectoral indices provided negative returns. This is in line with a priori expectations, due to the financial crisis, it is to be expected that such indices suffered from negative returns as the stock markets declined drastically. When it comes to the standard deviation, it can be noted that the Financials index was the riskiest, which makes sense since the Financials sector included the major banks which suffered from the most volatility. Whereas the consumers index was the least risky. The utilities sector displayed the highest kurtosis value, indicating that it suffered from the sharpest declines.

Covid-19 Crisis Period 03/02/2020 - 05/05/2023 (821 observations)	CNSM_US	COMM_US	ENRGY_US	FINC_US	HLTH_US	INDUS_US	MAT_US	TECH_US	UTIL_US
Mean	0.00023	0.00019	0.00068	0.00025	0.00039	0.00038	0.00012	0.00051	0.00001
Median	0.00053	0.00070	0.00105	0.00032	0.00037	0.00124	-0.00086	0.00105	0.00032
Maximum	0.08168	0.08384	0.14874	0.12360	0.07423	0.11913	0.16863	0.10449	0.12039
Minimum	-0.09867	-0.12126	-0.22491	-0.14745	-0.10382	-0.12041	-0.25908	-0.14487	-0.12056
Std. Dev.	0.01212	0.01723	0.02719	0.01942	0.01316	0.01691	0.02763	0.01987	0.01642
Skewness	-0.52155	-0.60198	-0.90441	-0.53600	-0.42389	-0.57372	-0.68936	-0.40717	-0.15856
Kurtosis	17.40045	8.63619	13.15321	14.12596	13.47087	13.85737	16.47082	9.37985	15.89308
Jarque-Bera	7131.10800	1136.27000	3638.38000	4273.86200	3775.15900	4077.59800	6272.57200	1415.05000	5689.94200

Table 4.6 - Descriptive Statistics of US Sectoral ETFs (Covid-19 Crisis Period)

When it comes to the Covid-19 crisis period, we can note higher mean values for all the sectors as compared to the financial crisis period. Standard deviation values seem to exhibit the same levels of riskiness as compared to the previous crisis. It can be noted that the materials and the energy sector suffered from the highest standard deviation. Kurtosis levels for this period seems higher than the financial crisis period, indicating that markets suffered from sharper declines.

4.4.3 Descriptive Statistics for Whole Sample – European Sectors

Table 4.6 outlines the descriptive statistics for the daily prices of all the nine sectors within Europe. Initially, it is noted that the Financials index has the highest standard deviation, followed by the Energy Index and the Materials Index, which is similar to the situation in the US, which makes sense since these three industries are cyclical sectors. In line with the US industry, the Consumers index has the smallest standard deviation.

Full Sample 17/11/2006 - 04/03/2024 (4350 observations)

	CNSM_EU	COMM_EU	ENRGY_EU	FINC_EU	HLTH_EU	INDUS_EU	MAT_EU	TECH_EU	UTIL_EU
Mean	0.0002	-0.0001	0.0000	-0.0002	0.0002	0.0003	0.0001	0.0003	0.0000
Median	0.0004	0.0002	0.0006	0.0000	0.0004	0.0007	0.0005	0.0008	0.0003
Maximum	0.0729	0.0856	0.1465	0.1633	0.0733	0.0992	0.1216	0.1081	0.0983
Minimum	-0.0975	-0.1139	-0.1873	-0.1639	-0.0945	-0.1281	-0.1489	-0.1313	-0.1518
Std. Dev.	0.0100	0.0119	0.0161	0.0189	0.0104	0.0142	0.0157	0.0155	0.0123
Skewness	-0.4288	-0.5202	-0.4861	-0.2367	-0.3378	-0.5936	-0.5230	-0.2683	-0.7476
Kurtosis	8.9359	11.4952	13.6554	11.4595	9.9482	10.9379	11.8845	8.5363	14.6995
Jarque-Bera	6519.65	13276.55	20749.88	13011.33	8833.08	11676.05	14505.08	5607.59	25214.31

Table 4.7 - Descriptive Statistics of European Sectoral ETFs (Full Sample)

When it comes to the Jarque-Bera Test, all industries also have a P-value of 0, and therefore one can reject the null hypothesis of a normal distribution for all industries, which means that the sectoral indices do not follow a normal distribution.

The two sectors that are considered to suffer from the highest level of skewness is the Utilities index and the Industrials index. When it comes to the kurtosis results, the European market seems to have suffered from lower levels of declines as compared to the US market. Here we can see that the Utilities Index followed by the Financials Index also suffered from the sharpest declines.

4.4.4 Descriptive Statistics for Different Time Periods – European Sectors

The below tables display the descriptive statistics for the European market during periods of distress:

Financial Crisis Period 01/03/2008 - 31/12/2012 (1176 observations)									
	CNSM_EU	**COMM_EU**	**ENRGY_EU**	**FINC_EU**	**HLTH_EU**	**INDUS_EU**	**MAT_EU**	**TECH_EU**	**UTIL_EU**
Mean	0.0004	-0.0002	-0.0002	-0.0004	0.0003	0.0001	-0.0003	-0.0001	-0.0005
Median	0.0008	0.0000	0.0006	-0.0005	0.0008	0.0007	0.0000	0.0006	-0.0003
Maximum	0.0729	0.0754	0.1042	0.1633	0.0733	0.0992	0.1216	0.1081	0.0983
Minimum	-0.0595	-0.0941	-0.0911	-0.1211	-0.0840	-0.1243	-0.1460	-0.1313	-0.1029
Std. Dev.	0.0113	0.0135	0.0178	0.0252	0.0114	0.0186	0.0217	0.0189	0.0153
Skewness	-0.1268	-0.0175	-0.0965	0.1799	-0.3042	-0.4417	-0.2140	-0.1772	-0.0495
Kurtosis	7.3168	8.5587	7.2393	7.8166	11.6122	8.2767	7.7263	8.2550	9.4915
Jarque-Bera	916.26	1514.12	882.44	1143.12	3652.45	1402.55	1103.53	1359.30	2065.31

Table 4.8 - Descriptive Statistics of European Sectoral ETFs (Covid-19 Crisis Period)

The mean results indicate that the sectors did not provide positive returns during the financial crisis period, which is in line with expectations. When it comes to the standard deviation, it can be noted that the Financials index was the riskiest, the same as with the US market. Furthermore, the standard deviation values are similar to that of the US, which shows that these two markets posed the same level of risk during the financial crisis. The same as with the US, the consumers index displayed the lowest level of risk. The Health Care sector displayed the highest kurtosis value, indicating that it suffered from the sharpest declines. The European market suffered from lower levels of kurtosis as compared to the US, indicating that US markets suffered from sharper declines.

Covid-19 Crisis Period 03/02/2020 - 05/05/2023 (821 observations)									
	CNSM_EU	**COMM_EU**	**ENRGY_EU**	**FINC_EU**	**HLTH_EU**	**INDUS_EU**	**MAT_EU**	**UTIL_EU**	**TECH_EU**
Mean	0.0000	-0.0001	0.0002	0.0002	0.0002	0.0002	0.0002	0.0000	0.0003
Median	0.0005	0.0009	0.0008	0.0007	0.0006	0.0012	0.0008	0.0003	0.0010
Maximum	0.0512	0.0856	0.1465	0.1157	0.0638	0.0934	0.0900	0.0581	0.1003
Minimum	-0.0975	-0.1139	-0.1873	-0.1554	-0.0945	-0.1281	-0.1489	-0.1518	-0.1163
Std. Dev.	0.0113	0.0124	0.0215	0.0208	0.0115	0.0162	0.0168	0.0137	0.0185
Skewness	-1.0637	-0.9783	-0.8613	-0.7543	-0.7782	-0.7101	-1.1403	-1.9533	-0.3025
Kurtosis	12.7215	16.9616	16.1765	10.4916	12.2040	10.5463	14.2303	22.8187	6.7355
Jarque-Bera	3387.77	6799.09	6040.75	1997.75	2980.78	2017.07	4492.28	13958.44	489.85

Table 4.9 - Descriptive Statistics of European Sectoral ETFs (Covid-19 Crisis Period)

Taking a look at the Covid-19 crisis period, we can also note higher mean values for all the sectors as compared to the financial crisis period. Standard deviation values also seem to exhibit the same levels of riskiness as compared to the previous crisis. The energy index and financial index displayed the highest standard deviation, as one would expect since they are considered to be cyclical sectors. Kurtosis levels for this period also seems higher as compared to the financial crisis period.

4.5 Correlation Analysis

Correlation can be defined as the correlation between members of observations ordered in time, if the data consists of time series data set. The correlation matrix is a measure which presents how such variables move together. The values range between -1.0 and 1.0. A correlation value of 1.0 implies that there is a perfect positive relationship between the two variables, while a correlation value of -1.0, implies that there is perfect negative correlation between the two variables. A correlation of 0 means that there is no correlation between the two variables, i.e. there is no relationship between the movement of the two variables.

Here correlation is a fundamental tool as it helps for relevant expectations. The Correlation Probability is calculated as:

$$\frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

The results are displayed below in the correlation probability tables, which outlines the connection and dependence each sector has with one another.

The below tables represent the correlation results between each sectoral index in Europe within the full data set, from 2006 up to 2023. This gives an indication as to whether the sectoral indices move in similar directions. The first thing that is noted, is that there is no negative correlation between each sector, which is in line with expectations since financial markets tend to move together.

Correlation									
	CNSM_EU	COMM_EU	ENRGY_EU	FINC_EU	HLTH_EU	INDUS_EU	MAT_EU	TECH_EU	UTIL_EU
CNSM_EU	1.0000	0.4853	0.3708	0.0609	0.5352	0.3928	0.3786	0.0601	0.4234
COMM_EU	0.4853	1.0000	0.4453	0.0495	0.4628	0.3671	0.4285	0.0363	0.4760
ENRGY_EU	0.3708	0.4453	1.0000	0.0726	0.4653	0.4166	0.4151	0.0359	0.3140
FINC_EU	0.0609	0.0495	0.0726	1.0000	0.0453	0.0763	0.0669	0.2294	0.0425
HLTH_EU	0.5352	0.4628	0.4653	0.0453	1.0000	0.3848	0.3787	0.0472	0.3729
INDUS_EU	0.3928	0.3671	0.4166	0.0763	0.3848	1.0000	0.4683	0.0808	0.3847
MAT_EU	0.3786	0.4285	0.4151	0.0669	0.3787	0.4683	1.0000	0.0834	0.3936
TECH_EU	0.0601	0.0363	0.0359	0.2294	0.0472	0.0808	0.0834	1.0000	0.0432
UTIL_EU	0.4234	0.4760	0.3140	0.0425	0.3729	0.3847	0.3936	0.0432	1.0000

Table 4.10 - - Correlation Matrix of European Treasury Bond ETFs

From the correlation table, it can be noted that the two sectoral indices that displayed the higher level of correlation is between the Health care index and the Consumer Services Index. Whereas the two sectoral indices which exhibited the lowest level of correlation is between the Energy index and the Technology index.

The below tables represent the correlation results between each sectoral indices in the US within the full data set, from 2006 up to 2023.

Correlation									
	CNSM_US	COMM_US	ENRGY_US	FINC_US	HLTH_US	INDUS_US	MAT_US	UTIL_US	TECH_US
CNSM_US	1.0000	0.6521	0.5285	0.6305	0.7383	0.7189	0.1930	0.7162	0.0141
COMM_US	0.6521	1.0000	0.6006	0.7110	0.6834	0.7555	0.2406	0.5683	0.0243
ENRGY_US	0.5285	0.6006	1.0000	0.6536	0.5711	0.7384	0.3549	0.5225	0.0085
FINC_US	0.6305	0.7110	0.6536	1.0000	0.6475	0.8111	0.1586	0.5205	-0.0136
HLTH_US	0.7383	0.6834	0.5711	0.6475	1.0000	0.7465	0.1902	0.6195	0.0052
INDUS_US	0.7189	0.7555	0.7384	0.8111	0.7465	1.0000	0.2508	0.6095	0.0165
MAT_US	0.1930	0.2406	0.3549	0.1586	0.1902	0.2508	1.0000	0.2736	-0.0444
UTIL_US	0.7162	0.5683	0.5225	0.5205	0.6195	0.6095	0.2736	1.0000	0.0037
TECH_US	0.0141	0.0243	0.0085	-0.0136	0.0052	0.0165	-0.0444	0.0037	1.0000

Table 4.11 - Correlation Matrix of US Treasury Bond ETFs

From the correlation table, we can note that although majority sectoral indices display positive correlation, a few exhibit a small level of negative correlation. It can be noted that the two sectoral indices that displayed the higher level of correlation is between the Financials index and the Industrials index and the two sectoral indices which exhibited the lowest level of correlation is between the Materials index and the Technology index.

Based on the correlation results, it is possible to form a few a priori expectations, specifically in relation to the connectedness results which will be obtained later on. Firstly, since the data on average exhibited elements of correlation, it is to be expected that there will be an element of connectedness between the different sectoral indices. Furthermore, the sectors that exhibit negative correlation can give an indication that there is no connectedness between the sectors.

Although correlation is a tool that provides useful and insightful information, it is important to distinguish between correlation and connectedness. The difference is that within a correlation function there is no direction, which means that the correlation between both variables will be the same. However, since connectedness is not a linear relationship, the values will be different measures for both ways, since the shocks from one sector and back do not affect each other in the same ways. This is because correlation only provides insight on pairwise associations (i.e. linear relationship) and does not provide information on how the shocks in one variable affect other variables, or how shocks surrounding one variable contributes to shocks into the system.

4.6 VAR Lag Selection Criteria

When using VAR, it is important that the following assumptions are satisfied; all data must have the same frequency, and data with different frequency must be converted into the same frequency so that all data has the same frequency. Furthermore, all the variables need to be stationary before carrying out the VAR, and therefore we can proceed since our data is stationary, otherwise a spurious model would be present. The output of the VAR is not relevant for the scope of this study, and therefore it is not presented in this paper.

In order to determine what order of VAR Lag should be used, the Akaike and Schwarz Bayesian models were generated. The Schwarz result shows a lag 0, however one cannot use lag 0 because the model won't work. Therefore, the Akaike should be taken into consideration which showed an order of lag 1, and thus this was used in order to achieve the most parsimonious model.

4.7 Conclusion

From the above initial steps, the first observation is that most of the industries were affected by the financial crisis as well as COVID-19 pandemic, where the financials and energy sectors seemed to be the most volatile. The descriptive statistics exhibit kurtosis, which indicates that the sectors are subject to outlier events. Furthermore, the descriptive statistics for the sub samples displayed higher standard deviations, which indicates higher levels of volatility during times of crises. The correlation analysis also provides some observations and information of the relationships between the sectoral indices. The results obtained in the chapter provide some initial information and aims to build on the results obtained in the next chapter.

Chapter 5 – Results and Analysis

5.1 Introduction

This chapter presents the empirical results obtained through the methodology previously outlined. These results aim to answer the main research questions outlined at the beginning of this paper, by applying the tools developed by Diebold and Yilmaz to measure connectedness. More specifically, this chapter looks at identifying the connectedness levels among the main sectors within financial markets in the US and Europe.

The below table provides details of the market capitalization at the end of 2006 and at the end of 2023 of the selected ETFs within the sample. The last two columns of the table outline the highest value of market capitalization that the ETFs have reached and in which year it was reached. Such values are denoted in millions.

Sector	Ticker	Market Cap 2006	Market Cap End of 2023	Year High	Market Cap High
Technology	VGT US	187.37	53,541.02	2023	53,541.02
Energy	XLE US	2,849.97	32,608.80	2022	38,155.26
Health Care	XLV US	1,396.73	34,016.77	2022	39,224.81
Materials	GDX US	334.45	11,679.27	2020	13,513.86
Financial	XLF US	1,708.11	30,813.22	2021	38,710.34
Industrials	XLI US	809.91	13,870.23	2021	15,405.58
Communications	VOX US	111.47	3,197.77	2021	3,693.25
Utilities	XLU US	2,270.24	12,800.18	2022	15,179.72
Consumer Staples	XLP US	1,129.96	13,725.14	2022	16,169.91
Technology	STK FP	10.74	73.69	2021	87.4
Energy	SXEPEX GY	187.00	921.69	2021	1234.1
Health Care	SXDPEX GY	212.47	647.44	2021	827.57
Materials	SXOPEX GY	18.47	105.24	2021	248.52
Financial	BNK FP	33.20	521.69	2021	1216.61
Industrials	SXNPEX GY	52.15	146.81	2020	533.39
Communications	SXKPEX GY	123.87	157.88	2019	672.95
Utilities	SX6PEX GY	75.70	252.60	2018	464.3
Consumer Staples	SX3PEX GY	29.45	244.41	2020	327.87

Table 5.1 - ETF Market Capitalization. Data Source: Bloomberg

As previously mentioned, the study covers the period between November 2006 to March 2024, which includes two prominent crises, that of the Global financial crisis of 2008, and the Covid-19 pandemic which broke out globally in 2020. This chapter shall be divided into the following sections, first we will look into the analysis of the static sample connectedness measure, which aims to look into the level of connectedness between the nine sectoral indices throughout the full sample period. Such observations look into the pairwise connectedness levels from the individual sectors and identify the stronger pairwise connectedness relationships. We shall also examine the dynamic nature of connectedness for the full sample which is based on the rolling sample estimation. The dynamic analysis looks into how connectedness changes over time and identifies whether there are any spikes in volatility during the sample. This approach will then be repeated for the crisis periods for both the US and European sectors. The rationale here is to measure the levels of connectedness during times of distress due to the crises.

5.2 Static Full Sample Connectedness US

This section looks into the static measure of connectedness for the whole sample period for all the sectoral indices between November 2006 to March 2024. Table 5.2 below displays the aggregate results for the US sectoral indices of the full sample 10-day forecasting period, while table 5.5 in the next section shows the results for the European sectoral indices. For both markets, the naturals logs for volatility were taken to approximate for normality. The table below is the same as the connectedness table presented in the methodology chapter and also includes an additional measure, that being the "net" result. This net result gives the difference between the "to" and "from" and provides information on which sectors are importers or exporters of volatility.

Taking a look at the first element in the connectedness table which is the overall connectedness in the system. The total sum of the 'From' column and the 'to' row measures the total overall system connectedness represented by the bottom-right figure of the below table, that is of

59.84%. This is a moderate level of connectedness since it is not a very high value but neither low. This implies that the volatility spillovers from other sectors cause a moderate amount of the forecast error variance within the system. This figure explains the average of the directional connectedness measures, them being the “to-others” or the “from-others” connectedness. A substantial level of connectedness was expected since the equity market is large and very liquid, which makes returns and market participants more connected.

Full Sample										
	CNSM_US	**COMM_US**	**ENRGY_US**	**FINC_US**	**HLTH_US**	**INDUS_US**	**MAT_US**	**UTIL_US**	**TECH_US**	**FROM**
CNSM_US	26.8	11.4	7.7	10.7	14.7	13.9	1	13.8	0	**73.2**
COMM_US	11.4	26.9	9.8	13.7	12.6	15.3	1.6	8.7	0	**73.1**
ENRGY_US	8.3	10.8	30	12.8	9.8	16.3	3.8	8.2	0	**70**
FINC_US	10.6	13.7	11.6	27	11.4	17.8	0.7	7.3	0	**73**
HLTH_US	14.5	12.4	8.8	11.2	26.9	14.9	1	10.2	0	**73.1**
INDUS_US	12	13.3	12.7	15.4	13	23.3	1.5	8.7	0	**76.7**
MAT_US	2.7	4.2	8.9	1.8	2.6	4.5	69.7	5.4	0.2	**30.3**
UTIL_US	15.8	10.1	8.6	8.4	12	11.5	2.4	31.2	0	**68.8**
TECH_US	0	0.1	0.1	0.1	0	0	0.2	0	99.5	**0.5**
TO	**75.5**	**75.9**	**68.1**	**74**	**76.1**	**94.2**	**12.4**	**62.2**	**0.3**	**59.84**
NET	**2.3**	**2.8**	**-1.9**	**1**	**3**	**17.5**	**-17.9**	**-6.6**	**-0.2**	

Table 5.2 - Connectedness Table Full Sample US

On a system wide level, it can be seen that the Technology sector (0.3%) has no contribution to the other sectors. Furthermore, the Materials sector has the lowest contribution to others at a level of 12.4%, which is pretty small when compared to the rest of the other sectoral indices. On the other hand, the Industrials sector (94.2%) is subject to the highest shocks.

The diagonal values represented in grey, will typically be the highest values in the table since they are the shocks that are coming from within themselves which represents the volatility coming from their own shocks. It can be seen that each sector’s own volatility is the highest contributor to its forecast error variance. Although the connectedness measures here are the highest values out of the connectedness table, they are still rather low, which means that the sectoral ETFs receive a high level of shocks from other sectors. The own connectedness of the Technology sectoral index (99.50%), it is very interesting since it only receives shocks from within itself and is not affected by shocks from other sectors. This however is in line with the correlation matrix outlined in the descriptive statistics chapter, as it is barely correlated with any other sector. A reason for this could be that Technology can behave as a cyclical or defensive stock depending on the industry and therefore might be subject to their own shocks while other sectors do not impact it. The Technology sector (0.3%) has no contribution to the other sectors, while the other 'own connectedness' results obtained range from 23.3% to 69.7%. Besides the Technology and Materials sector, none of the own connectedness results are larger than the "to" or "from" total figures (the bold figure). This implies that the majority of the sectors are highly connected to the rest of the sectors, which means that each sector is more impacted by the other sectors rather than themselves.

When it comes to the pairwise connectedness measure (denoted by $C_{i\leftarrow j}^{H}$), the highest value observed is from the industrial sector to the financial sector; $C_{FIINC\,US \leftarrow INDUS\,US}^{H} = 17.8\%$. The reverse of this is $C_{INDUS\,US \leftarrow FINC\,US}^{H} = 15.4\%$, which is also one of the highest variables observed for pairwise connectedness. This makes sense since these two sectors are cyclical sectors and therefore more subject to shocks since they are more sensitive towards the business cycle. Another reason why these two sectors are highly connected is due to the use of commodity derivatives, which increases especially during times of uncertainty, therefore sending shocks to each other. The second highest pairwise connectedness is also between the Industrials sector to the Energy sector; $C_{ENRGY\,US \leftarrow INDUS\,US}^{H} = 16.3\%$, which is in line with the results obtained by Manicaro (2023). The Industrials sectors and Energy sector are heavily connected since these two sectors form part of the production process.

Moving onto the results obtained in the 'From' column and 'To' row, which measures the directional connectedness of the sectors. The sum of each row in table 5.2 portrays the total directional connectedness that each sectoral ETF receives, shown in the 'From' column. Each summation outlines the percentage share of volatility that each sectoral ETF received from the other sector during the total sample. The ‘From’ column therefore shows the total forecast error variance which is 100% minus the ETFs own connectedness value. Excluding the Technology industry (since the value is 0.5%), the ‘From’ variables range from 30.30% to 76.70%. Therefore, the Industrial sector is the sector subject to the most shocks from the system, while the Technology sector and Materials sector are subject to the least shocks.

The ‘To’ column represents the sum of the pairwise connectedness that each sectoral ETF has on the system. Contrary to the ‘From’ connectedness previously mentioned, a sector’s contribution to the other sectors forecast error variance is not limited to 100% and therefore the total ‘To’ connectedness can be larger than 100%. Again, excluding the Technology sector since the value is only 0.3, the ‘To’ connectedness ranges from 12.40% to 94.2 %. Here we can see that the Industrials sector also has the greatest ‘To’ connectedness; 94.20% which means not only does it receive a substantial amount of shocks from the other sectors, but also transmits a large amount of shocks to other sectors. After the Industrials sector, the Communications sector displays the second largest value. Looking at the smallest value, the Technology sector does not transmit any shocks, while the Materials sector barely transmits any shocks to other sectors. Excluding the Technology sector and Materials sector, the results obtained from the connectedness in the ‘From’ column are relatively similar since, ranging between 68.8% to 76.7%. When it comes to the results from the connectedness transmitted to others, the range is a bit wider, between 62.2% to 94.20 (excluding Technology and Materials).

Moving to the last result, the ‘Net’ values, which represents the net total directional connectedness denoted by $C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H}$. As previously mentioned in the Methodology chapter, a sectoral ETF can either be an exporter or importer of volatility. These results range between -17.90% up to 17.50%. We note a significant positive value for the Industrials Sector (17.50%), which is no surprise since it also had the highest ‘To’ and ‘From’ connectedness value. This positive figure means that the Industrials sector is the largest exporter of volatility, since it transmits more shocks than it receives. The Health (3%), Communications (2.8%), Consumers (2.3%) and Financials (1%) sectors emit low shocks into the system. It was expected that the Health and Consumers sector would have a stable level since they are defensive sectors and not subject to high volatility. The Materials Industry displayed the highest negative net total directional connectedness (-17.9%), which makes sense since it registered the lowest level of ‘From’ and ‘To’ connectedness (excluding the Technology Sector). This implies that the Materials industry the largest net receiver/ importer of volatility, implying that it is heavily influenced by the movements in the price of other sectors. The Utilities displays the second highest negative value (-6.6%), while the Energy sector comes in third with a small net amount (-1.9%).

5.3 Dynamic Connectedness US Full Sample

The static connectedness measure described above provides an accurate measure, however it only provides connectedness in one single measure. The static measure does not provide information on the dynamics of connectedness within the sample. The dynamic approach applies a rolling sample estimation which takes into account the assumption that connectedness and spillover levels change over time throughout the sample period. This will help provide information on how connectedness and volatility shocks between the sectors changed over time. Figure 5.1 below displays the rolling total spillover index, where a rolling estimation window width of 200 days with a 10 day forecast horizon was used for all the different samples. The connectedness levels in the below figure ranges between 30% to 75%, with the majority of the period ranging between 50% to 70%, which is in line with the connectedness level of 59.84% established from the static measure.

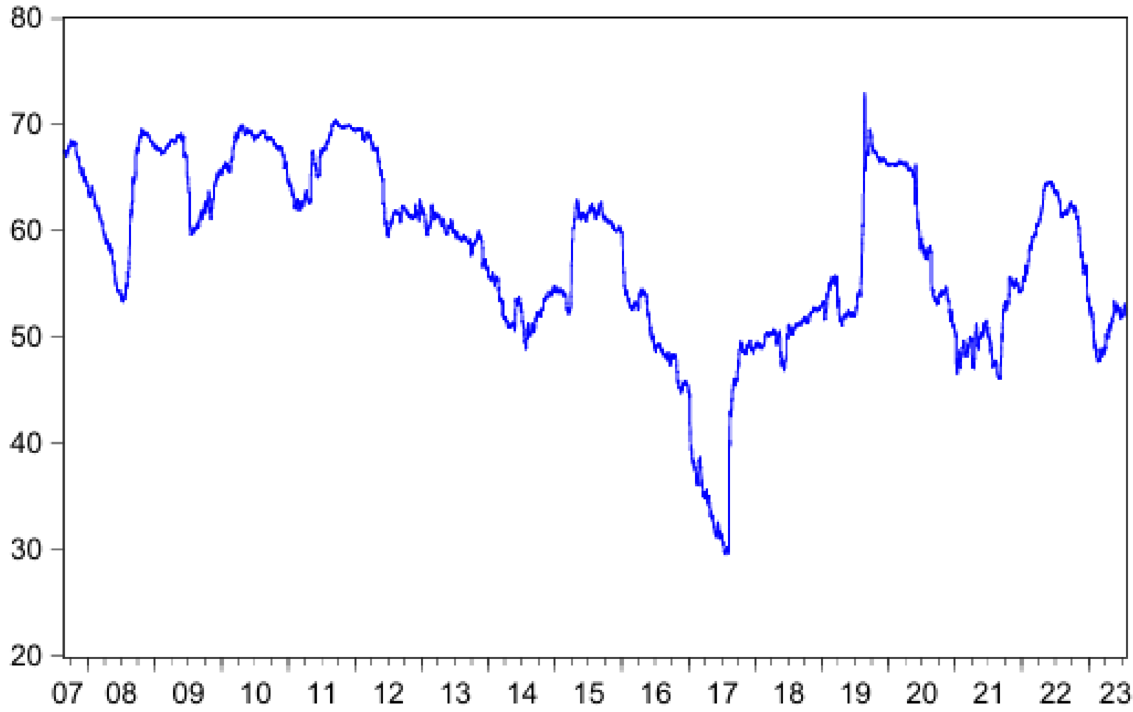

Figure 5.1 – Dynamic Connectedness Full Sample US

Upon examining the above graph, we can note that volatility spiked around the financial crisis and European sovereign debt crisis period. There is a further spike, reaching the highest level of volatility at around the time that the Covid-19 crisis broke out. This is in line with previous literature which noted that volatility spillovers increase during times of economic distress which results in higher connectedness levels. Furthermore, between the period of 2012 (when the economy started to recover from the Financial and European sovereign debt crisis) to 2017, the connectedness level on average was declining, ranging between 60-30%, which further supports the argument that volatility spillovers tend to decrease during tranquil times. During this period, we can note a spike in connectedness during 2015. Although during this period there was no significant crisis, this spike could be a result of the selloffs in the stock market, where people were selling their stocks and turning towards safer assets such as fixed income and gold. This resulted from the "concerns about economic growth and the effectiveness of central banks' policies"

Randall & Gaffen (2016). Another reason as to why connectedness could have increased in 2015 is due to the collapse of the Chinese Stock market and it is also the year that the ECB's program to buy back government bonds started. In 2017 we also see sharp increase in connectedness which could be attributed to when Bitcoin broke value records and when there was a sharp increase in US rates and Donald Trump's tax reform which increased volatility. A decline in connectedness can also be noted after 2020, when the economy started to recover from Covid-19 crisis, which is in line with the study carried out by Imran, Saba and et al. (2023). We also note a spike in volatility in 2022, which does make sense since there were positive spikes in prices the markets experiencing after the Covid-19 pandemic. This can be supported by the market capitalization outlined in table 5.1 which shows that the majority of the selected ETFs reached their highest level of market capitalization in 2022, which would have increased volatility within markets. This can also be supported by the price charts in the descriptive statistics chapter which show that the price for all the US sectoral ETFs increased significantly, excluding the Communications and Utilities sectors which did not benefit from this increase in price.

5.4 Static US Financial Crisis Period Connectedness

Financial Crisis Period										
	CNSM_US	**COMM_US**	**ENRGY_US**	**FINC_US**	**HLTH_US**	**INDUS_US**	**MAT_US**	**TECH_US**	**UTIL_US**	**FROM**
CNSM_US	22.5	12.9	11	10.7	14.1	14	1.7	0	13	**77.5**
COMM_US	12.1	21.2	12.4	13.1	12.1	14.5	2.6	0	11.9	**78.8**
ENRGY_US	10.3	12.7	21.9	10.3	10.9	14.2	6.4	0	13.3	**78.1**
FINC_US	11.6	15.1	11.7	24.6	10.6	15.8	1.7	0.1	8.8	**75.4**
HLTH_US	14.3	13	11.4	9.8	23	14	2.3	0.1	12.2	**77**
INDUS_US	12.8	14	13.4	13.2	12.6	20.5	3.1	0	10.5	**79.5**
MAT_US	3.7	6.3	15	3.5	4.9	7.6	51.3	0.5	7.3	**48.7**
TECH_US	0.2	0.3	0.6	0.7	0.4	0.3	0.9	96.2	0.4	**3.8**
UTIL_US	13.1	12.9	14.2	8.4	12.4	11.9	3.4	0.1	23.5	**76.5**
TO	**78.1**	**87.3**	**89.6**	**69.5**	**77.9**	**92.4**	**22.2**	**0.9**	**77.4**	**66.16**
NET	**0.6**	**8.5**	**11.5**	**-5.9**	**0.9**	**12.9**	**-26.5**	**-2.9**	**0.9**	

Table 5.3 - Connectedness Table Financial Crisis Sample US

The above table represents the static connectedness measures for the Financial crisis period. The overall connectedness measure in the system is 66.16%, which has increased as compared to the full sample connectedness. This is in line with what Diebold and Yilmaz found throughout their 2014 paper, that during times of financial distress, volatility spillovers and in turn connectedness is said to increase. The diagonal entries during the crisis have all declined by about 2% to 10%. This is to be expected since shocks coming from other variables tends to increase during times of volatility. As expected, the Technology sector (96.2%) followed by the Materials sector (51.3%) have the highest levels of 'own' connectedness although to a slightly lesser extent. The Industrials sector (20.5%) also has the lowest level of 'connectedness' during this period, followed by the Communications sector (21.2%).

When it comes to pairwise connectedness, we can note that the highest level of connectedness (15.8%) is from the Industrials sector to the Financials sector, the same as with the whole sample period. Interestingly, the second highest pairwise connectedness is from the Communications sector to the Financials sector (15.1%), rather than from the Industrials sector to the Energy sector as in the full sample period. During this period the Industrials sector is also the highest pairwise exporter of volatility to other sectors. The lowest levels of pairwise connectedness (excluding the Technology sector) are from the Materials sector to the Financials sector (1.7%). Looking at the 'From' and 'To' results, we can note that of course the Technology sector (3.8%) is basically not subject to shocks coming from other sectors, nor does it transmit shocks to other sectors as seen from the 'To' result (0.9%). This could be attributed to the size of this sectoral ETF, since it has the largest market capitalization, and therefore may not be affected by movements in the other ETFs. The Materials sector (48.7%) also does not receive a significant amount of spillover effects, however during the financial crisis we note that the level of connectedness with other sectors has increased from 30.3%. There is also an increase in how much the Materials sector transmits shocks to other sectors, as this level increased to 22.2%. This behaviour is due to the sector being a cyclical sector and depends on the business cycle, which would be impacted during times of crises.

Taking a look at the 'Net' results, we can note a mix of results as the levels here have increased for some sectors and decreased for some sectors as compared to the whole sample. The

Materials sector is still the sector that is affected by the most spillovers from other sectors, however at a higher level which is to be expected since volatility spillovers increase in times of distress. The Industrials sector is still the largest exporter of volatility however to a lesser extent. The Energy sector during this timeframe was another main transmitter of volatility (11.5%), while during the whole sample it was a receiver of volatility (-1.9). This increase in transmission of shocks to the system could be attributable to the period were the demand for oil declined and in turn affected other sectors such as industrials, materials, consumers and utilities. We also note the same behaviour for the Utilities sector but to a lesser extent (0.9% vs -6.6%). The Consumers, Health Care and Utilities sectors all have the smallest 'net' values during this sample, which may be due to the fact that these sectors are defensive sectors (non-cyclical) which means that they have low sensitivity even during times of crises, and therefore it makes sense that such sectors would not transmit or receive many shocks.

5.5 Dynamic US Financial Crisis Period Connectedness

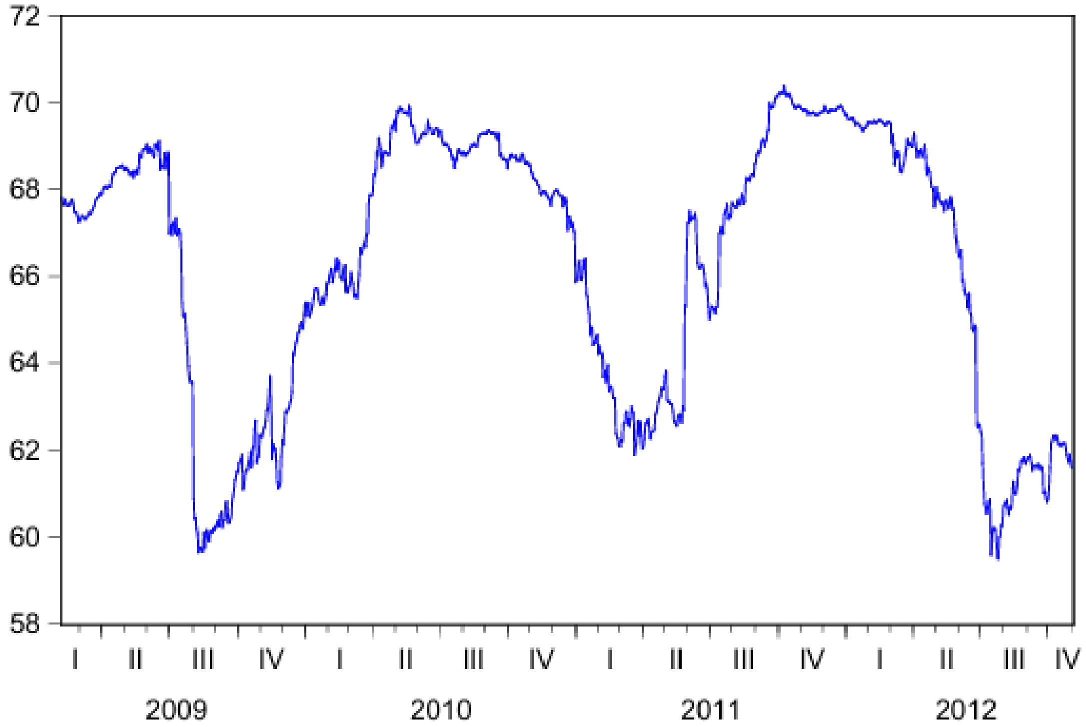

Figure 5.2 - Dynamic Connectedness Financial Crisis Sample US

Figure 5.2 displays the rolling sample connectedness during the financial crisis and Sovereign debt crisis period. During this period we can see that the connectedness levels have increased and ranges between 60%-70% as compared to the full sample, which is line with the increased level of static connectedness. This is also consistent with past studies and as previously mentioned, connectedness has increased during times of crises. We can see that there is a spike in volatility connectedness in 2009, where it then gradually declines and spikes again in 2011, which can be explained by the Sovereign debt crises and then gradually declines again.

5.6 Static Covid-19 Period Connectedness US

Covid-19 Period										
	CNSM_US	**COMM_US**	**ENRGY_US**	**FINC_US**	**HLTH_US**	**INDUS_US**	**MAT_US**	**TECH_US**	**UTIL_US**	**FROM**
CNSM_US	25.1	9.8	5.3	12.2	16.1	13.9	1.7	0.4	15.4	**74.9**
COMM_US	11.3	28.5	6.6	14.4	14	14.9	1.8	0.4	8.1	**71.5**
ENRGY_US	7.1	7.2	33.5	18	8.6	17	2	0.3	6.4	**66.5**
FINC_US	11.3	11.3	12.5	23.3	12.3	19.1	0.7	0.2	9.4	**76.7**
HLTH_US	15.5	11.7	6.1	12.8	24.9	13.8	1.9	0.6	12.7	**75.1**
INDUS_US	12.4	11.3	11.2	18.3	12.8	21.8	1.3	0.3	10.6	**78.2**
MAT_US	4.5	4.4	4.2	1.9	4.1	4	71.9	0.2	4.9	**28.1**
TECH_US	0.5	0.1	0.2	0.2	0.4	0.4	0.4	97.2	0.5	**2.8**
UTIL_US	17.1	7.9	5.2	11.4	14.8	13.2	2.3	0.4	27.7	**72.3**
TO	**79.7**	**63.7**	**51.4**	**89.3**	**83**	**96.3**	**12**	**2.7**	**67.8**	**60.68**
NET	**4.8**	**-7.8**	**-15.1**	**12.6**	**7.9**	**18.1**	**-16.1**	**-0.1**	**-4.5**	

Table 5. 4 - Connectedness Table Covid-19 Crisis Sample US

Table 5.4 presents the connectedness levels during the Covid-19 crisis. Here we can see that the overall connectedness measure in the system is 60.68% which is slightly higher than the level for the whole sample, which is in line with the results obtained by Costa, Matos and Silva (2020). The ‘own’ connectedness levels are similar to the whole sample levels, and slightly higher than the financial crisis levels. As expected, the Technology sector (97.2%) is only responsive to shocks within the sector, and the Materials sector (71.9%) coming in second with a higher level than the financial crisis sample and full sample. The Industrials sector (21.8%) again has the smallest level, however coming in second is the Financials sector (23.3%). When it comes to pairwise connectedness, the highest level exhibited is again from the Industrials sector to Financials sector (19.1%). The second highest pairwise connectedness level is from the Financials sector to the Industrials sector (18.3%), while in the full sample the Industrials sector transmitted more shocks to the Financials sector. Taking a look at the ‘From’ results obtained in the above table, these are very similar to the whole sample and financial crisis period. Here we can note that Communications, Energy, Materials and Utilities sector became importers of volatility during this period as opposed to exporters like during the financial crisis period. Furthermore, we can note that the Materials sector (-16.1% vs -26.5%) was subject to less shocks from other sectors during this period.

When looking at the net results for the three samples, we can note that the Industrials sector (18.1%) is the largest exporter of volatility. Since the Industrials sector is a broad sector of the economy and provides capital goods to other sectors and therefore affecting the manufacturing and end-process production. This sector also contains some of the largest companies in the economy, which can further explain the transmissions of shocks into the system. The Materials sector (-16.1%) is the largest importer of volatility in all three samples which could be attributed to the fact that since it is a cyclical sector it is more volatile and sensitive to shocks within and outside the system. Coming in second, the Energy sector (-15.1%) also is one of the main net receiver of shocks, which can be supported by the results obtained by Goutte, Guesmi and Uorm (2022), who found that the pandemic had the biggest affect in co-movements between the energy commodity market and the stock market. We can conclude that on average the figures in the connectedness table follow a similar trait as observed in the Financial crisis period.

5.7 Dynamic US Covid-19 Period Connectedness

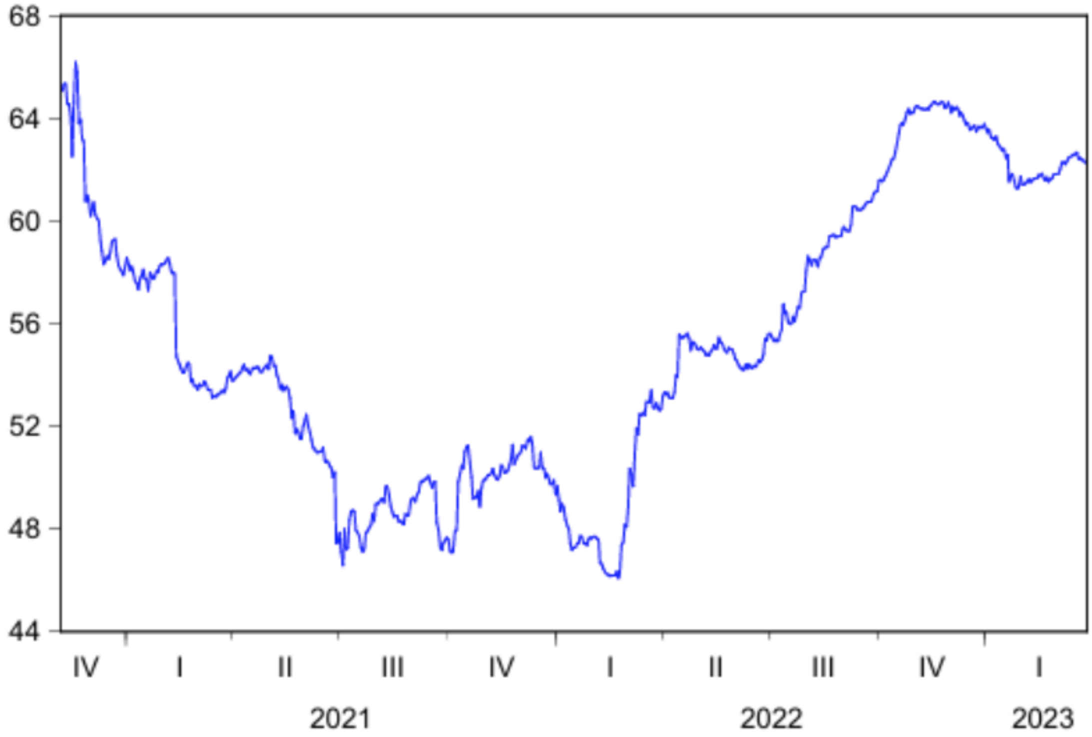

Figure 5.3 - Dynamic Connectedness Financial Covid-19 Sample US

Figure 5.3 displays the rolling sample connectedness during the Covid-19 crisis period, where the level of dynamic connectedness remained high throughout the sample and ranges between 45% to 65%. This is also in line with the study carried out by Cotsa, Matos and Silva (2020) who found that connectedness remained high until the end of Covid. Here we can see that initially connectedness has increased, however then started to decline towards 2022, and then started to increase rapidly towards 2023. The decline noted towards 2022 could be attributed towards the economy adjusting to Covid-19 and therefore volatility stabilizing. Then once the economy started to recover and financial markets started to experience an increase in prices volatility started to increase leading to connectedness increasing, supported by the increase in market capitalization during 2022.

5.8 Static EU Full Sample Connectedness

Full Sample										
	CNSM_EU	COMM_EU	ENRGY_EU	FINC_EU	HLTH_EU	INDUS_EU	MAT_EU	TECH_EU	UTIL_EU	FROM
CNSM_EU	46.5	11	6.4	0.2	13.3	7.2	6.7	0.2	8.6	53.5
COMM_EU	10.7	45.3	9.1	0.1	9.7	6.2	8.4	0.1	10.5	54.7
ENRGY_EU	6.9	9.9	49.8	0.3	10.8	8.6	8.6	0.1	4.9	50.2
FINC_EU	0.4	0.5	0.6	92.2	0.2	0.5	0.4	4.9	0.4	7.8
HLTH_EU	13.3	9.9	10.1	0.1	46.3	6.9	6.7	0.2	6.6	53.7
INDUS_EU	7.7	6.8	8.9	0.3	7.5	50.1	11	0.3	7.4	49.9
MAT_EU	7.1	9.1	8.5	0.2	7.1	10.8	49.2	0.4	7.7	50.8
TECH_EU	0.4	0.2	0.1	5	0.2	0.7	0.7	92.5	0.2	7.5
UTIL_EU	9.5	11.7	5.7	0.1	7.4	7.4	7.9	0.1	50.3	49.7
TO	55.8	59	49.2	6.2	56.2	48.3	50.3	6.3	46.4	41.98
NET	2.3	4.3	-1	-1.6	2.5	-1.6	-0.5	-1.2	-3.3	

Table 5. 5 - Connectedness Table Full Sample EU

The above table presents the European ETF sectoral sample connectedness covering the full period. The overall connectedness for the EU is lower compared to the US with a result of 41.98%, therefore from such results we can note that US markets have a higher level of connectedness when compared to European markets. When it comes to the ‘own’ connectedness results, we can note that again the Technology sector has the highest level of own connectedness (92.5%). In line with the Technology sector is the Financials sector with a connectedness level of 92.2%, which is much higher when compared to the Financials sector in the US. Furthermore, all the sectors show a higher level of ‘own’ connectedness as compared to the US and ranges between 46.3% up t0 50.3% (excluding Tech and Finc). Therefore, since the EU shows higher levels of ‘own’ connectedness we would expect pairwise connectedness levels to be lower, as displayed above. The highest pairwise relationship is from the Consumer sector to the Health sector (13.3%) and interestingly the same from the Health sector to the Consumer sectors. The smallest pairwise connectedness is from the Energy sector to the Technology sector, from the Financials sector to the Communications, Health and Utilities sectors and from the Technology sector to Comminutions, Energy and the Utilities sectors, all displaying a result of 0.1%.

Looking at the results obtained in the ‘From’ total directional connectedness column, we note lower figures as compared to the US sample. The results here range between 54.7% to 7.5%, with the majority ranging in the fifties area. The Communications sector seems to transmit the highest level of shocks to the other sectors, while the Health sector comes in second at a close level of 53.7%. Furthermore, as expected the Technology sector displays the lowest level of ‘from’ of 7.5%, with the Financials sector coming in as a close second with a figure of 7.8%. The lowest ‘To’ total directional connectedness is noted for the Financials sector (6.2%) and then the Technology sector (6.3%), which is notably lower than the rest of the sectors. The Communication sector has the highest ‘To’ total directional connectedness at 59% and therefore has the highest net total directional connectedness, making it the largest net transmitter of stock volatility to the other sectors. The Utilities sector has the highest negative **net** total directional connectedness values both at -1.6%, making it the largest net receiver of stock volatility from the other sectors.

5.9 Dynamic EU Full Sample Connectedness

Figure 5.4 - Dynamic Connectedness Full Sample US

The above figure outlines the dynamic connectedness between the sectors within Europe. Here we can note a larger range of 10% up to 75%, as compared to the US sectors. We can note that initially the overall connectedness level is much smaller and then spikes sharply once the Financial crisis starts. We can then note that that once the connectedness level reached approximately 60% in 2012, the fluctuations in connectedness are smaller and range between 30 points as compared to the US sector, which ranged between 45 points. Overall the US and European sectors both display the same highest level of connectedness at about 75%.

5.10 Static EU Financial Crisis Period Connectedness

Financial Crisis Period										
	CNSM_EU	COMM_EU	ENRGY_EU	FINC_EU	HLTH_EU	INDUS_EU	MAT_EU	TECH_EU	UTIL_EU	FROM
CNSM_EU	77.3	7	4.8	0.1	6.9	0.6	0.7	0	2.6	22.7
COMM_EU	6.5	71.4	7.3	0.5	6.2	0.4	3.3	0	4.5	28.6
ENRGY_EU	4.1	6.7	66.4	0.4	17.8	1.9	2.6	0	0	33.6
FINC_EU	0.1	0.7	0.5	97.6	0.1	0.3	0.1	0.1	0.5	2.4
HLTH_EU	6	5.9	18.2	0.1	68	0.5	0.9	0.1	0.4	32
INDUS_EU	0.7	0.3	3.4	0.1	0.9	92.1	1.3	0.2	1	7.9
MAT_EU	0.7	4.1	3.5	0.1	1.2	1.4	87.1	0.1	1.8	12.9
TECH_EU	0.1	0.1	0.1	0.1	0	0.2	0.1	99.2	0.1	0.8
UTIL_EU	4.7	5.7	5.6	0.1	2.3	0.8	1.7	0.2	79	21
TO	22.8	30.5	43.4	1.4	35.4	6	10.7	0.7	11	17.99
NET	0.1	1.9	9.8	-1	3.4	-1.9	-2.2	-0.1	-10	

Table 5.6 - Connectedness Table Financial Crisis Sample EU

Looking at the results obtained from the connectedness table (Table 5.6) for the Financial crisis period, we can note a low level of overall connectedness (17.99%) which is much lower than in the full sample. However, from the dynamic analysis this low level makes sense because at the beginning of the sample the dynamic connectedness was only approximately 10% thus on average this lowers the connectedness level for the sample. When it comes to 'own' connectedness, again the Technology sector (99.2%) and the Financial sector (97.6%) have the highest values here meaning they are not subject to shocks outside their own sector. On average we can note that 'Own' connectedness is higher than the full sample as it ranges from 68% to 92.1% (excluding Tech and Finc). Therefore, we can argue that during the financial crisis period the sectors were mostly influenced from their own shocks. This is further supported by the low results obtained from the 'From' and 'To' connectedness. The Energy Sector was mostly affected by shocks coming from the other sectors and gave off the most shocks as it had the highest 'From' (33.6%) and 'To' (43.4%) results, which is further supported by the lowest 'own' connectedness results. During the Financial crisis, oil and gas were influenced by the depreciation of the Euro vs US dollar and affected sectors related in the end-production process.

5.11 Dynamic EU Financial Crisis Period Connectedness

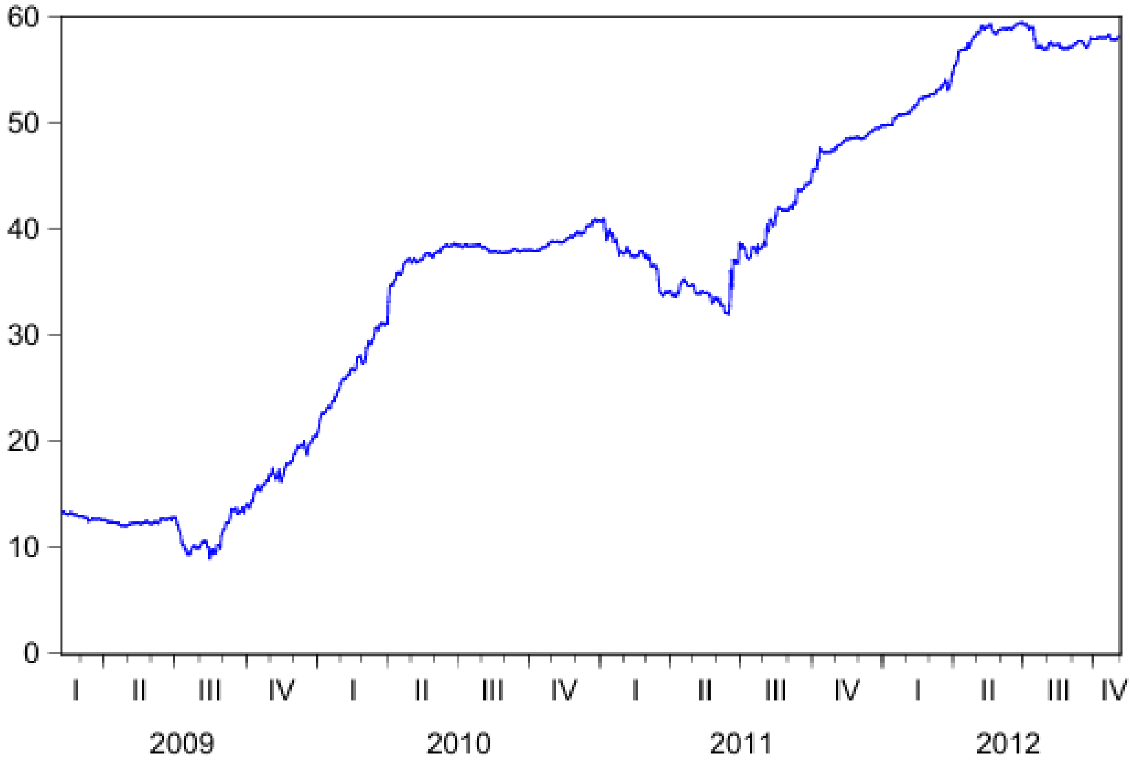

Figure 5. 5 - Dynamic Connectedness Financial Crisis Sample EU

Figure 5.5 displays the dynamic connectedness between the European sectors during the financial crisis and Sovereign debt crisis. In line with expectations and past literature, we can see a rapid increase in connectedness, starting from approximately 10% up to 60%. As compared to the US markets, we can see that there was a sharper increase in connectedness within European, although ultimately within the same level of 60%. Also, in line with past literature, we can see that within the US connectedness started to decline in 2012, whereas the European sectors continued to increase, which suggests that the European Sovereign debt crisis had a larger impact on European sectors as compared to the US.

5.12 Static EU Covid-19 Period Connectedness

	Covid-19 Period									
	CNSM_EU	COMM_EU	ENRGY_EU	FINC_EU	HLTH_EU	INDUS_EU	MAT_EU	UTIL_EU	TECH_EU	FROM
CNSM_EU	25.3	12.7	6	0.6	14	13.7	14.2	12.6	0.8	74.7
COMM_EU	13.1	26.1	9.5	0.6	10.6	12.4	13.6	13.7	0.4	73.9
ENRGY_EU	8.1	12.3	34	0.4	6	14.3	14.4	10.3	0.2	66
FINC_EU	1.7	1.5	1.1	65.7	1.2	3.1	2.5	1.3	22	34.3
HLTH_EU	16.1	11.8	5.2	0.4	28.8	12.4	12.1	12.4	0.8	71.2
INDUS_EU	12.5	10.9	9.7	1	9.7	23	20.3	11.2	1.9	77
MAT_EU	12.8	11.8	9.6	0.8	9.4	20	22.7	11.7	1.2	77.3
UTIL_EU	13.1	13.9	8	0.5	11.3	12.8	13.6	26.4	0.5	73.6
TECH_EU	2.5	1.1	0.3	21.1	2.2	5.2	3.7	1.1	62.8	37.2
TO	80	75.9	49.3	25.2	64.5	94	94.3	74.3	27.8	65.03
NET	5.3	2	-16.7	-9.1	-6.7	17	17	0.7	-9.4	

Table 5.7 - Connectedness Table Covid-19 Crisis Sample EU

The results obtained in table 5.7 for the Covid-19 crisis sample shows that overall connectedness within the system is 65.03%, which is a substantial increase from the previous two samples observed. The overall connectedness for this period is also higher than the overall connectedness observed for the US sample. Interestingly enough, although overall connectedness has increased, the 'own' connectedness figures have decreased ranging between 22.7% to 65.7%, which suggests that the sectors were more subject to shocks coming from outside the system. Another interesting point is that, from all the samples within both markets, the Technology sector comes in second highest when it comes to 'own' connectedness, with a much lower level (62.8%) as previously observed. The Financials sector (65.7%) has the highest 'own' connectedness, whilst the Materials sector (22.7%) and Industrials sector (23%) has the lowest 'own' connectedness results.

We can note that initially connectedness within the European sectors was low and most of their shocks were coming from within. Towards the end of the full sample, we can see that the shocks coming from within themselves shifted, and connectedness 'From' (ranging between 34.3% to 74.7%) and 'To' (ranging between 25.2% to 94.3%) increased making the behaviours and patterns here more similar the connectedness behaviour of the US sectors. It could be argued that financial markets within different markets have become more integrated. The Materials sector (77.3%) and the Consumers sector (74.7%) is subject to the most shocks from the system, while the Financials sector (34.3%) and Technology sector (37.2%) are subject to the least shocks. The sector that gives off the most shocks to the other sectors are the Materials sectors (94.3%) and the Industrials sector (94%), making them the largest exporters of shocks to the system, both having net values of 17%. Such results are to be expected since these two sectors rely heavily on the cycle of the economy making them more volatile. The energy sector is the largest importer of shocks (-16.7%), which can also be explained by the results obtained by Goutte, Guesmi and Uorm (2022), who found that the pandemic had the biggest affect in co-movements between the energy commodity market and the stock market.

5.13 Dynamic EU Covid-19 Period Connectedness

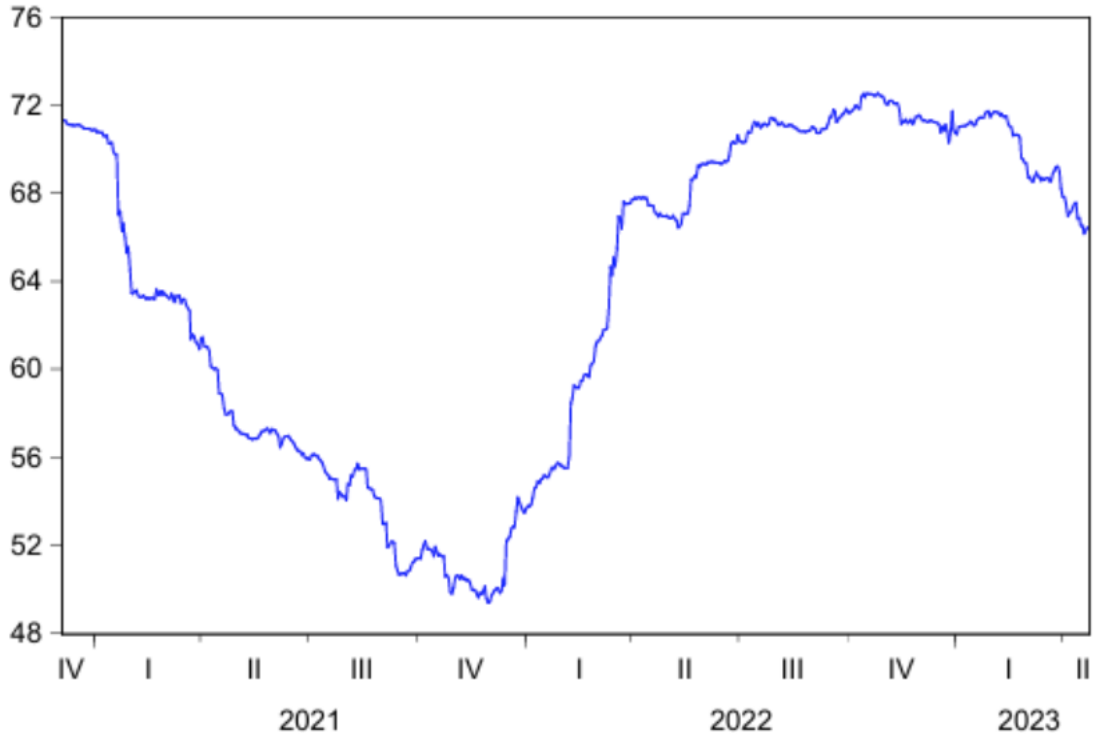

Figure 5.6 - Dynamic Connectedness Covid-19 Sample EU

Figure 5.6 displays the rolling sample connectedness during the Covid-19 crisis period for the European sectors, where the level of dynamic connectedness ranges between 45% to 70%. We can observe relatively the same pattern for volatility connectedness as with the US sample. This is in line with the static connectedness figures, which display similar behaviours as well. Specifically how volatility connectedness is high and declines gradually towards the late 2021 and beginning of 2022 and how then it increases later on in 2022 and then seemed to settle between the 70% range. As previously mentioned, in 2022 the market capitalization of the sectoral ETFs rose to their all-times highs, which is supported by the price graphs in the descriptive statistics chapter which show a spike in prices, and therefore can explain the increase in volatility spillovers.

5.14 Conclusion

The results obtained throughout this chapter provide an understanding into the notion of volatility connectedness between the major sectors within the US and Europe. Such findings outline that there is a substantial level of connectedness within the sectors however it isn’t too extreme. The results infer that volatility spillovers increase during times of financial crises. More specifically we can note that the European sectors initially did not exhibit high levels of connectedness but as time progressed this increased, implying that contagion has increased. Furthermore, interestingly enough Technology seemed to be the sector not subject to volatility spillovers from other sectors, but also during times of distress and both with US and European markets.

Chapter 6 – Conclusion

6.1 Main Findings and Objectives

The main objective of this paper was to analyse and assess the connectedness level between the major different sectors within developed markets and to understand which sectors are more vulnerable during times of distress. The first objective was to understand the overall connectedness levels between the different sectors and to see whether these findings are in line with past literature. The static full sample connectedness resulted in a level of 59.84% for the US sectors and 41.98% for the European sectors, thus showing a moderate level of connectedness for the two markets, with US having a higher level. Such results of connectedness and an increase in connectedness during times of distress are in line with the findings of Diebold and Yilmaz (2011,2012,2014), Balcilar, Elsayed, Hammoudeh (2023), and Laborda and Olmo (2021).

The second objective was to identify pairwise connectedness between the different sectors and identify possible reasons for such findings. The results obtained here show varying levels of directional connectedness measures. The highest pairwise connectedness in the US was noted from the Industrials sector to the Financials sector, with a level of 17.8%, 15.8% and 19.1% within each respective sample. This is attributed to the two sectors being part of the production process and both being cyclical sectors making them subject to the business cycle. Within the European sample, the highest pairwise connectedness was between the Health Care sector (13.3%) and the Consumers sector (13.3%) with both having the same levels 'from' and 'To' within the full sample, and from the Health Care sector to the Energy sector (17.8%) in the financial crisis sample and from the Consumers sector to the Health care sector (16.1%) in the Covid-19 sample. The Health care sector was heavily influenced by the Covid-19 pandemic and therefore shocks from the sector would tend to increase.

The third objective was to identify which sectors are net transmitters and net receivers of volatility. When it came to the US sample, the results showed that in the financial crisis sample the Industrials (12.9%) and Energy (11.5%) sectors were the largest net transmitters of spillover effects, while the main net receivers were the Materials (-26.5%) and the Financials (-5.9%) sectors. During the Covid-19 crisis sample, the main net transmitters of shocks was again the Industrials sector (18.1%), however coming in second was the Financials sector (12.6%). Costa, Matos and Silva (2020) also found the Financials sectors to be one of the main "relevant sender of connectedness during the pandemic". A possible reason as to why the Financials sector was one of the main transmitters is because during the financial crisis, the Banking sector in the US was more affected by cyclical sectors. The main net receivers were the Materials sectors (-16.1%), the same as during the financial crisis period although to a lower extent, and the Energy sector. Such findings can be attributed to these sectors being cyclical sectors and therefore being more sensitive towards the business cycle and customer spending. Within the European sample, during the financial crisis the main net transmitter of shocks was the Energy sector (9.8%) (the same as with the US sample and of a similar level) and the Health Care Sector (3.4%). The main net receivers of shocks were the Utilities sector (10%) and the Material sector (-2.2%). Such results obtained here are lower than the US. During the Covid-19 period, the main net transmitters were the Materials and Industrials sector, both having a level of 17%, while the main net receivers were the Technology sector (-9.4%) since it always had low results and the Energy sector (-16.7%).

Another objective was to analyse the dynamic connectedness during the whole data set and the connectedness based in the US and Europe. The dynamic connectedness analysis provided insightful information and helped in understanding the static connectedness results. The dynamic approach shows how connectedness changed over time throughout each sample. It further confirmed results obtained in past literature, as it showed spikes in connectedness in the times of crises or periods of volatility. It also provided a visual representation of the connectedness behaviour and showed similar patterns between the US market and European market.

The last objective was to analyse the levels of connectedness during the different time periods of financial distress, and to see if there were any similarities in the connectedness levels between the two crises. When it comes to the overall connectedness within the system, US sectoral connectedness increased slightly in the financial crisis period and the Covid-19 crisis period, which is in line with past literature. Interestingly, when it came to the European sectors, connectedness increased substantially during the Covid-19 pandemic, however, was lower in the Financial crisis period as opposed to the full sample. This seemed strange at first, however the dynamic connectedness analysis provided an answer to this discrepancy. At the beginning of the sample, before the financial crisis broke out, connectedness within the system in European markets seemed low, at a level of approximately 10% and then started to increase rapidly. Therefore, the full sample takes into account this low level of connectedness which pushes down the average connectedness within the Financial Crisis sample as well as the full sample.

6.2 Implications of Findings

This study finds that sectoral connectedness increases during periods of distress. Connectedness and spillover effects within different sectors can help in understanding the potential repercussions that periods of financial distress and high volatility have on financial markets. This can be particularly useful when it comes to risk managers, policy makers, portfolio managers and market participants. Such findings can be helpful in terms of downside risk, risk management? and investment diversification, by using this information when designing portfolio construction, asset allocation and rebalancing portfolios and can also provide useful information when it comes to hedging. Looking at pairwise connectedness and which sectors are net receivers and net transmitters of shocks when designing a portfolio of assets or rebalancing a portfolio, can help in achieving the optimal diversified portfolio which suffers from less shocks during times of economic turbulence.

The findings show that the US Technology sector seems to be highly unconnected from the rest of the system as it does not transmit nor receive shocks from the other sectors. Therefore, adding a portion of Tech stocks or Technology ETFs to a portfolio, will not only provide returns (as shown by the increase in market capitalization and price) but will also provide diversification in times of crises and therefore limits downside risk. Furthermore, adding a portion of defensive sectors to the portfolio does prove to be beneficial such as Health care, Consumer Staples and Utilities which could provide a level of stability during times of distress and increased volatility since these sectors were low net transmitters and net receivers of shocks even during the Financial Crisis and Covid-19 crisis periods in both the US and Europe, which can be supported by the fact that they are low-beta sectors. Furthermore, these sectors are prominent in the economy and risk managers and portfolio managers should monitor these sectors closely, as they might give off early signals of distress.

Looking at the pairwise connectedness information can also be helpful when it comes to diversification and also for hedging purposes. For example, if looking for diversification benefits, one might opt to choose sectors which have low pairwise connectedness, such as the Technology since it exhibited the lowest levels of pairwise connectedness, the Materials sector with Consumers, Health Care or Financials sectors. When it comes to hedging purposes, looking at the spillover and connectedness information among the sectors can be helpful. Looking at which pairs are the receiver-transmitter and the transmitter-receiver and which sectors are not integrated between the full sample and crises samples can help in providing a profitable hedging strategy. Connectedness information can also help policy makers understand spillover effects between sectors in order to minimize systemic risk to the financial system as a whole and in turn establish economic policies and regulations.

6.3 Avenues for Future Research

The methodology that Diebold and Yilmaz created on studying the volatility spillovers and connectedness relationships created a framework for many studies and topics of research, spanning between different asset classes, different sectors, different economic variables within different markets and regions. Applying different economic variables, such as inflation, interest rates or GDP and analysing the connectedness with different sectors or market classes could provide important macroeconomic insights which can be used in large VAR systems.

One could expand this research to different regions, such as the Asian market which would be particularly interesting for the Covid-19 sample, since the pandemic originated from China. It would also be interesting to see how less developed markets or emerging markets reacted to the Financial crisis and the Covid-19 pandemic, such as South Africa, Mexico, Brazil, South Korea and Turkey. Would shocks within different sectors still transmit to one another in less developed markets? Another interesting domain would be to analyse the connectedness relationships between different markets, such as fixed income, equity, forex and commodities markets during times of crises.

Instead of using daily stock price data, one could apply this methodology by using “high-frequency intra-day data”, which Diebold and Yilmaz used in their early studies. Using a different frequency can provide insight into whether the results change or whether findings are still in line when using different frequency data. One can also analyse connectedness between different sectors by extending this methodology were one can apply a multivariate GARCH-BEKK model and create spillover indices, which is the technique used by Mile Ivanov (2014).

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Appendices

Appendix 1 - Descriptive Statistics - Original ETF Returns

	CNSM_US	COMM_US	ENRGY_US	FINC_US	HLTH_US	INDUS_US	MAT_US	UTIL_US	TECH_US
Mean	47.540	84.496	68.025	22.380	71.308	59.539	33.497	47.507	162.338
Median	49.300	84.710	68.920	20.950	69.710	54.970	30.560	44.570	105.850
Maximum	80.570	150.660	101.290	42.120	147.860	125.960	66.630	78.120	528.370
Minimum	19.410	35.480	23.570	5.018	21.880	15.360	12.470	22.740	29.270
Std. Dev.	16.784	21.939	14.277	8.742	36.650	25.960	12.131	13.301	128.701
Skewness	0.135	0.592	-0.385	0.253	0.439	0.461	0.588	0.281	1.063
Kurtosis	1.769	3.569	2.925	2.018	1.918	2.104	2.390	1.904	2.794
Jarque-Bera	288.181	312.519	108.709	221.126	352.183	299.557	318.387	274.775	827.516

Table A.1 - Descriptive Statistics for US ETF returns

	CNSM_EU	COMM_EU	ENRGY_EU	FINC_EU	HLTH_EU	INDUS_EU	MAT_EU	TECH_EU	UTIL_EU
Mean	54.621	25.609	32.263	21.497	66.769	45.128	39.816	57.819	33.749
Median	60.660	25.140	32.360	20.135	70.620	42.435	39.605	48.240	32.045
Maximum	88.660	39.530	48.240	54.940	114.500	83.350	70.930	143.880	56.750
Minimum	19.870	15.592	15.408	9.160	27.630	15.090	15.750	17.930	24.490
Std. Dev.	18.312	5.032	4.895	8.288	23.966	15.852	12.241	29.851	6.718
Skewness	-0.204	0.535	0.144	2.391	0.102	0.411	0.339	0.800	1.270
Kurtosis	1.695	2.635	4.003	9.140	1.754	2.265	2.293	2.528	4.236
Jarque-Bera	340.720	232.936	198.479	11033.870	290.309	221.550	174.771	506.677	1454.342

Table A.2 - Descriptive Statistics for EU ETF returns

Appendix 2 - Augmented Dickey-Fuller Unit Root Tests

Null Hypothesis: CNSM_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-72.83153	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.3 - ADF Unit root test - Consumers US

Null Hypothesis: COMM_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-69.60914	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.4 - ADF Unit root test - Communications US

Null Hypothesis: ENRGY_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-70.41791	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.5 - ADF Unit root test - Energy US

Null Hypothesis: FINC_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-74.14290	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.6 - ADF Unit root test - Financials US

Null Hypothesis: HLTH_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-71.73816	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.7 - ADF Unit root test - Health Care US

Null Hypothesis: INDUS_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-69.66755	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.8 - ADF Unit root test - Industrials US

Null Hypothesis: MAT_US has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-50.06182	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.9 - ADF Unit root test - Materials US

Null Hypothesis: TECH_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-71.91226	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.10 - ADF Unit root test - Technology US

Null Hypothesis: UTIL_US has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-72.44204	0.0001
Test critical values:	1% level	-3.431670	
	5% level	-2.862008	
	10% level	-2.567062	

Table A.11 - ADF Unit root test - Utilities US

Null Hypothesis: CNSM_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-29.52590	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.12 - ADF Unit root test - Consumers EU

Null Hypothesis: COMM_EU has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.39834	0.0000
Test critical values:	1% level	-3.438110	
	5% level	-2.864855	
	10% level	-2.568589	

Table A.13 - ADF Unit root test - Communications EU

Null Hypothesis: ENRGY_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.36967	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.14 - ADF Unit root test - Energy EU

Null Hypothesis: FINC_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.54988	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.15 - ADF Unit root test - Financials EU

Null Hypothesis: HLTH_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-29.18049	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.16 - ADF Unit root test - Health Care EU

Null Hypothesis: INDUS_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.50745	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.17 - ADF Unit root test - Industrials EU

Null Hypothesis: MAT_EU has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.49412	0.0000
Test critical values:	1% level	-3.438110	
	5% level	-2.864855	
	10% level	-2.568589	

Table A.18 - ADF Unit root test - Materials EU

Null Hypothesis: TECH_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-29.32983	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.19 - ADF Unit root test - Technology EU

Null Hypothesis: UTIL_EU has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.81704	0.0000
Test critical values:	1% level	-3.438100	
	5% level	-2.864850	
	10% level	-2.568587	

Table A.20 - ADF Unit root test - Utilities EU

Appendix 3 - Kwiatowski-Philips-Schmidt-Shin (KPSS) Unit Root Tests

Null Hypothesis: CNSM_US is stationary
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.043603
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: COMM_US is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.085965
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: ENRGY_US is stationary
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.060186
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: FINC_US is stationary
Exogenous: Constant
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.343450
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: HLTH_US is stationary
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.105859
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: INDUS_US is stationary
Exogenous: Constant
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.093820
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: MAT_US is stationary
Exogenous: Constant
Bandwidth: 20 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.057017
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: TECH_US is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.193446
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: UTIL_US is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.051030
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: CNSM_EU is stationary
Exogenous: Constant
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.092411
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: COMM_EU is stationary
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.086600
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: ENRGY_EU is stationary
Exogenous: Constant
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.143679
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: FINC_EU is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.138087
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: HLTH_EU is stationary
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.047176
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: INDUS_EU is stationary
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.083109
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: MAT_EU is stationary
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.061010
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

Null Hypothesis: TECH_EU is stationary
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.071470
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Table A.21 - KPSS Unit root test - Utilities EU

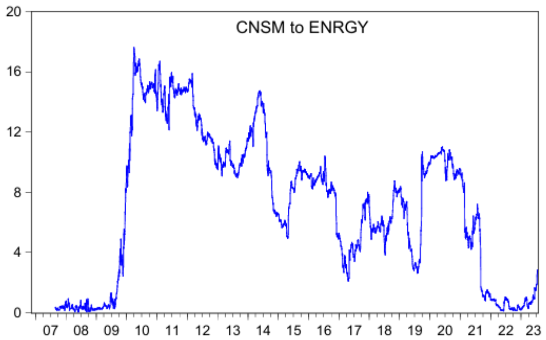
Null Hypothesis: UTIL_EU is stationary
Exogenous: Constant
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

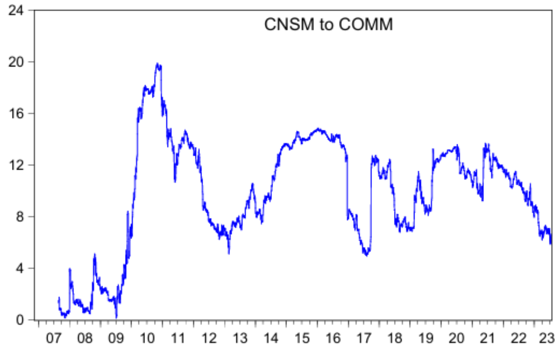
		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.044075
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

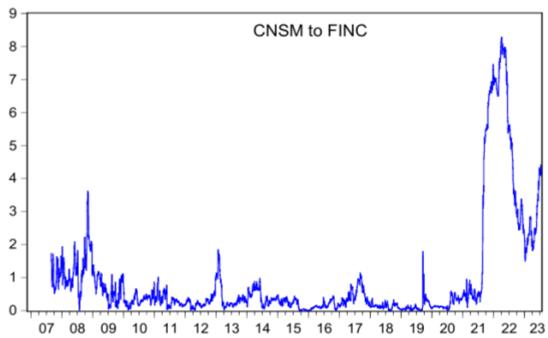
Table A.21 - KPSS Unit root test - Utilities EU

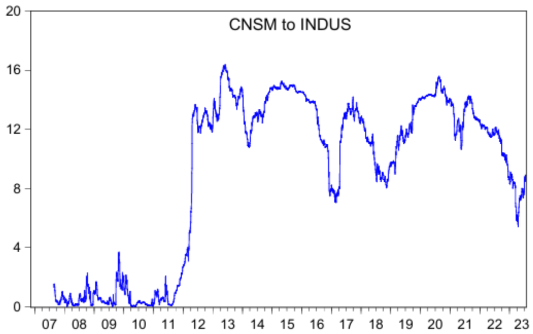
Appendix 4 – Dynamic Connectedness

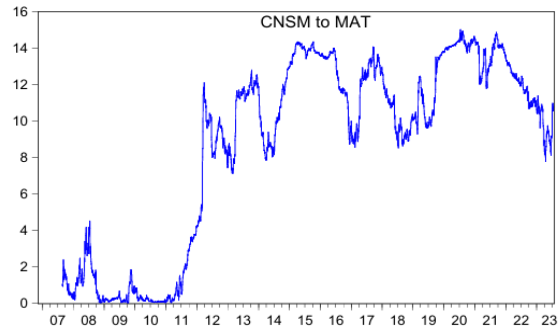
Sample Period 1 – Full Dynamic Connectedness EU Sectors

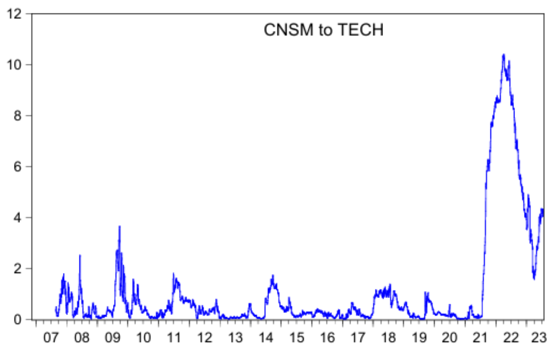


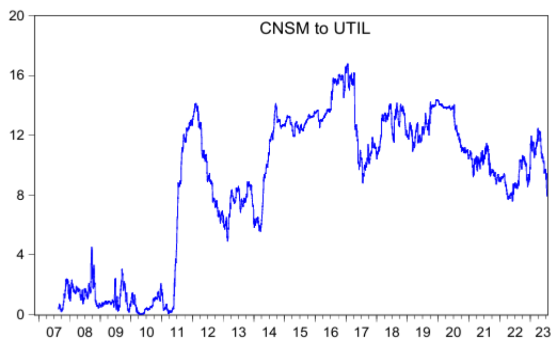


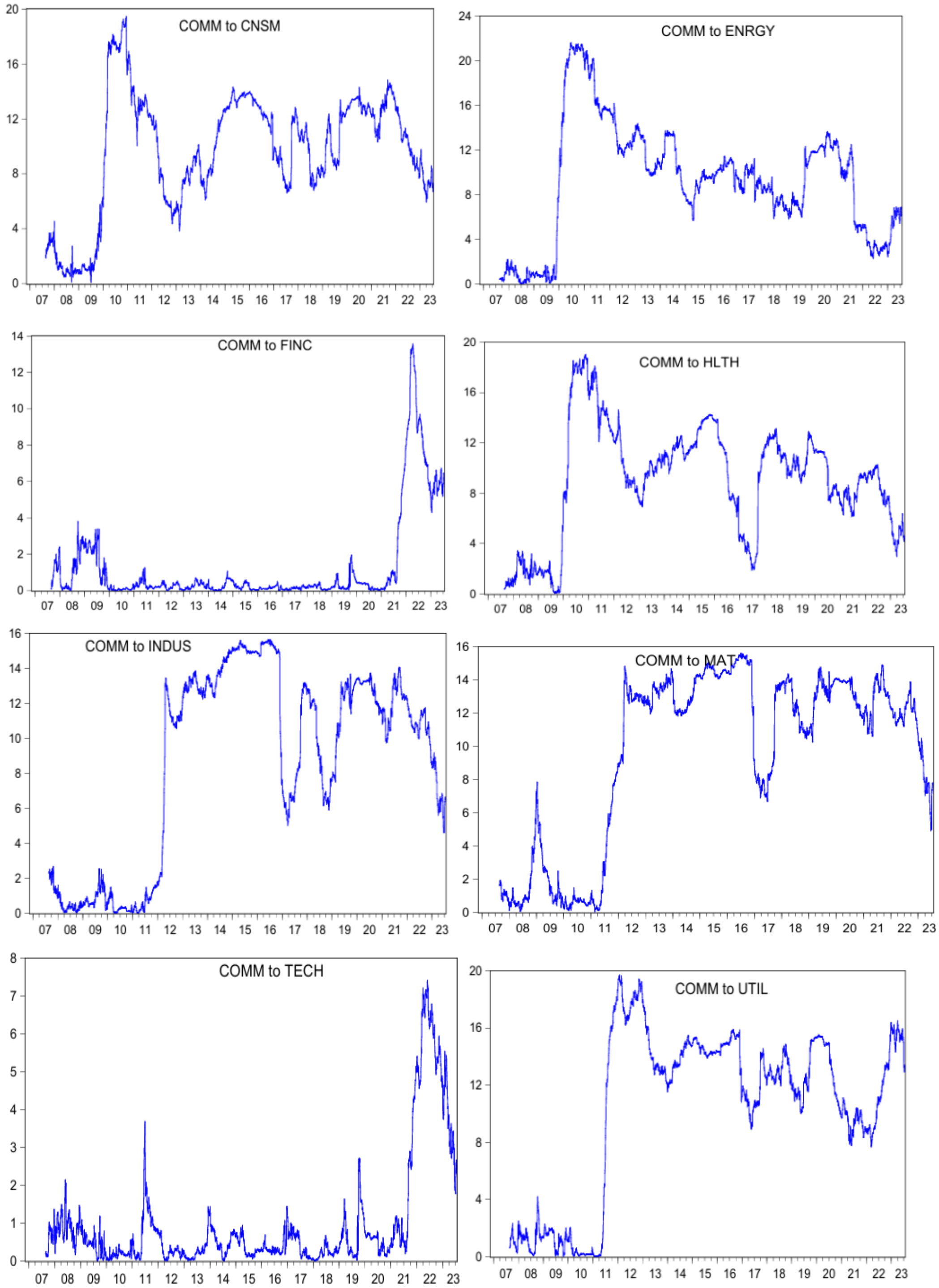


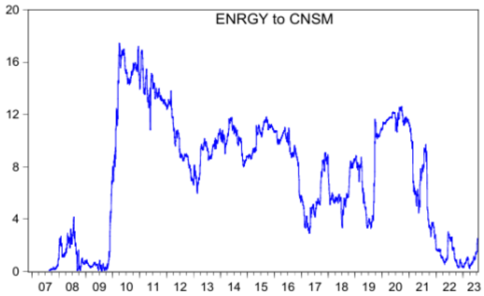









COMM to CNSM
COMM to ENRGY
COMM to FINC
COMM to HLTH
COMM to INDUS
COMM to MAT
COMM to TECH
COMM to UTIL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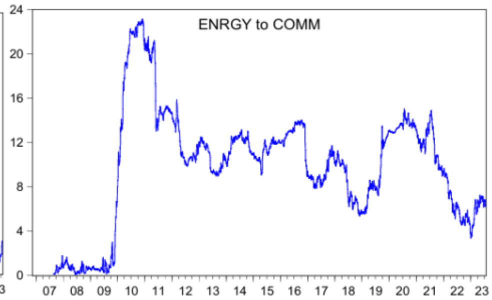
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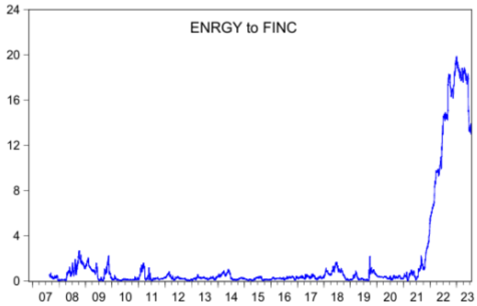
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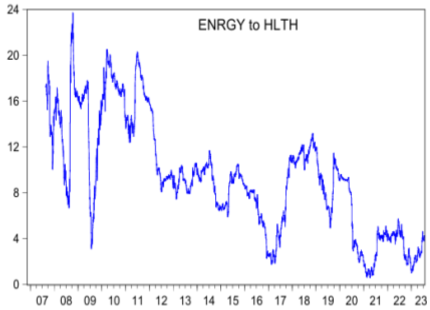
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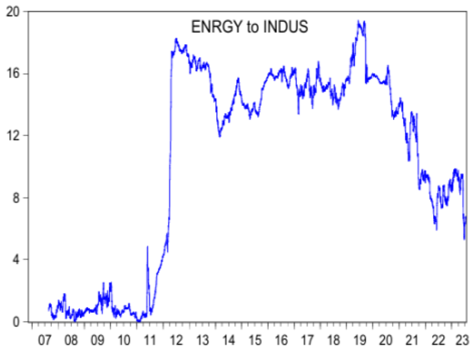
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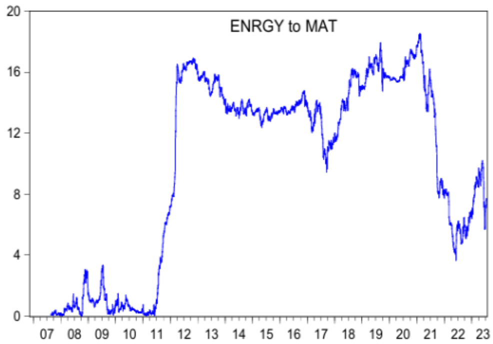
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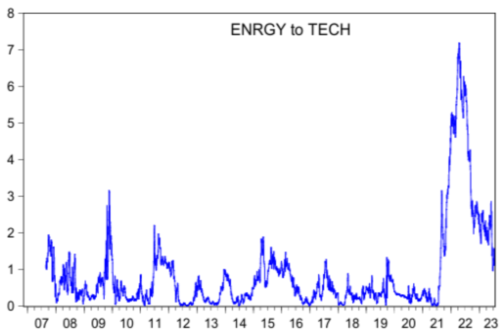
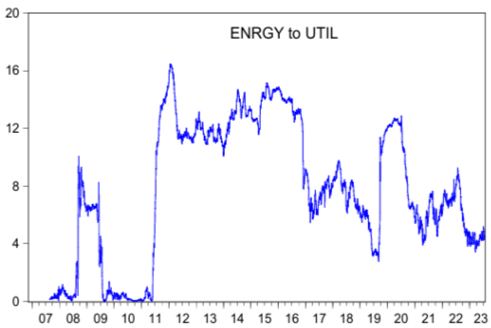
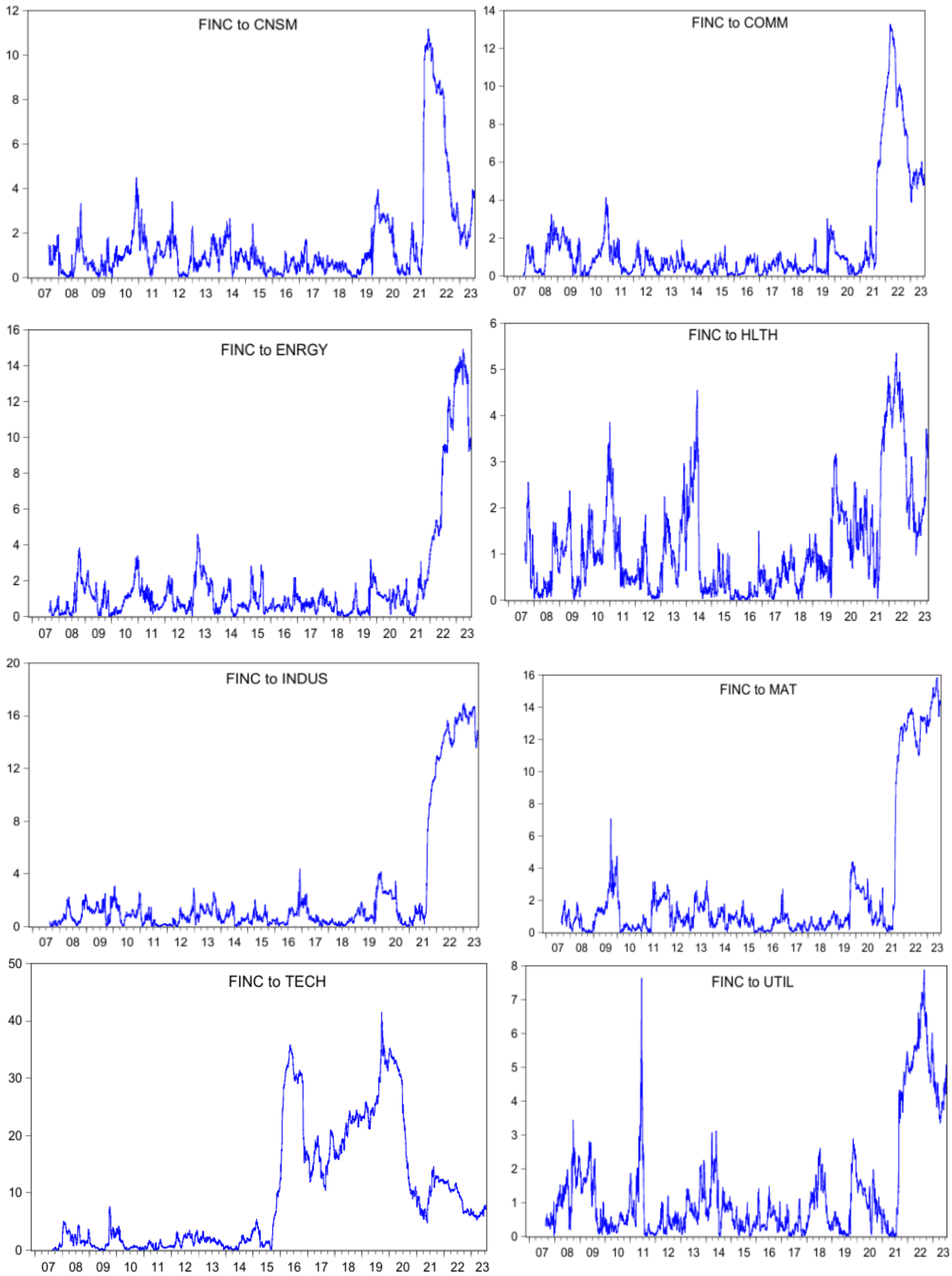

ENRGY to TECH


ENRGY to UTIL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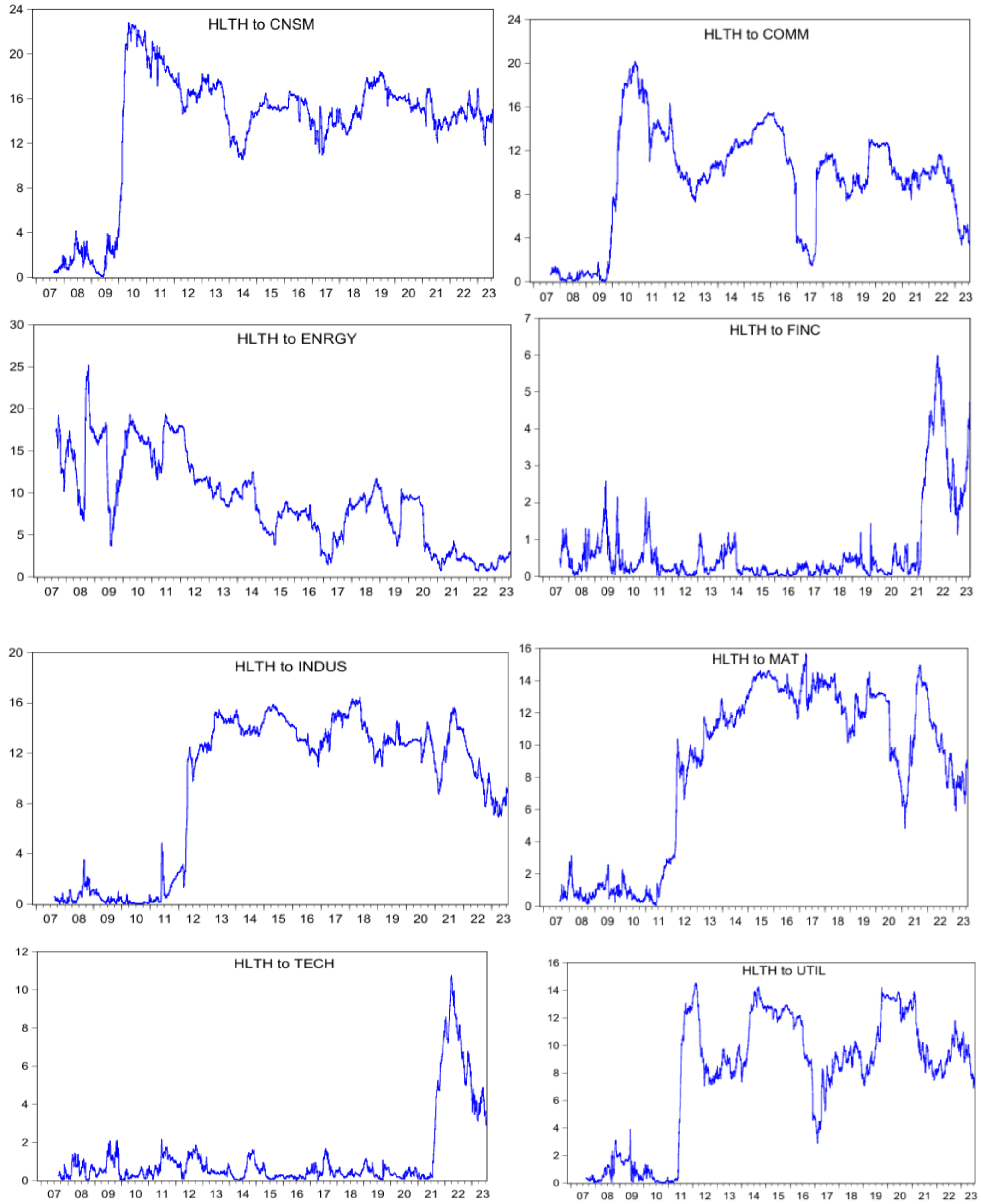
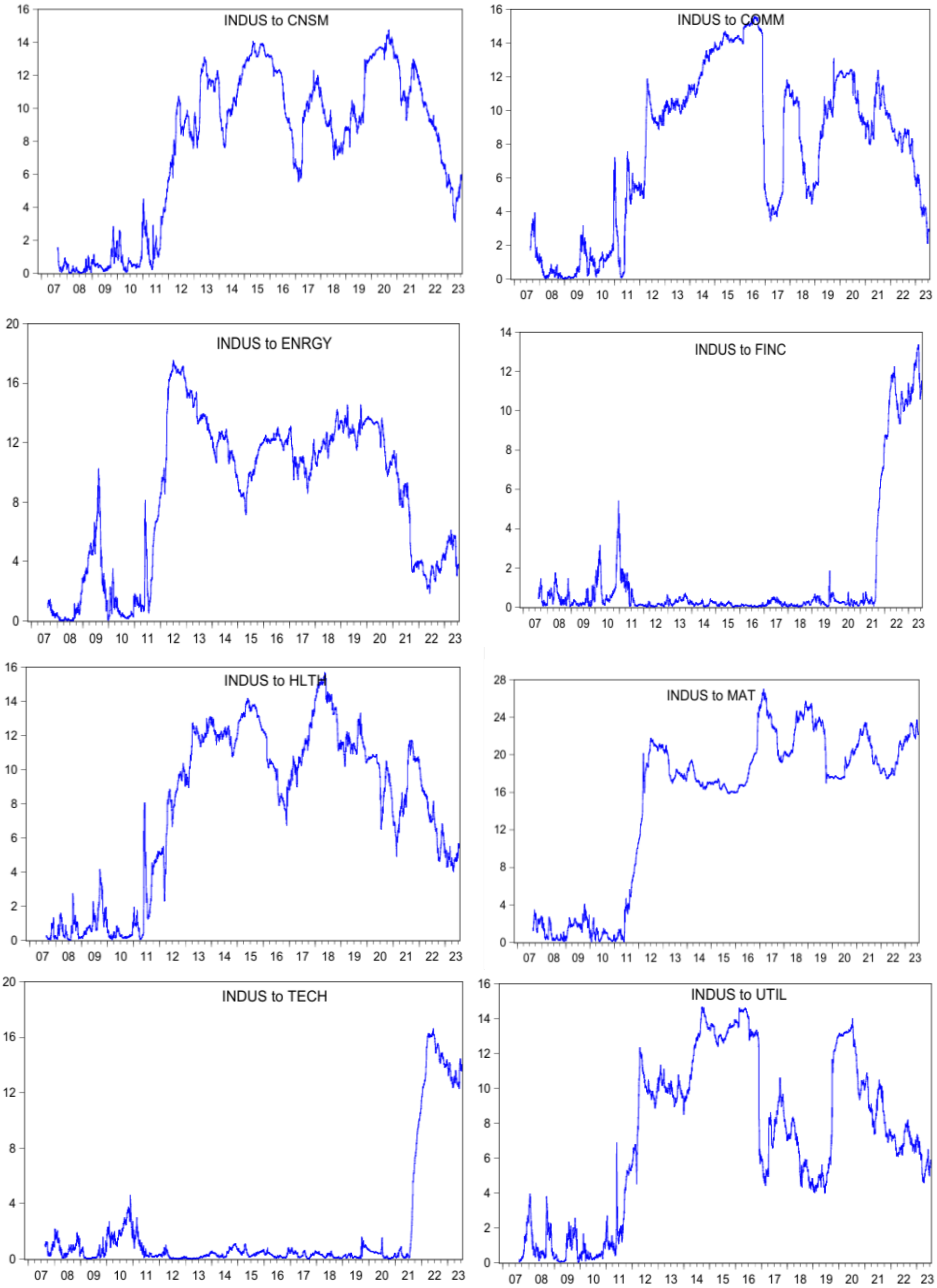
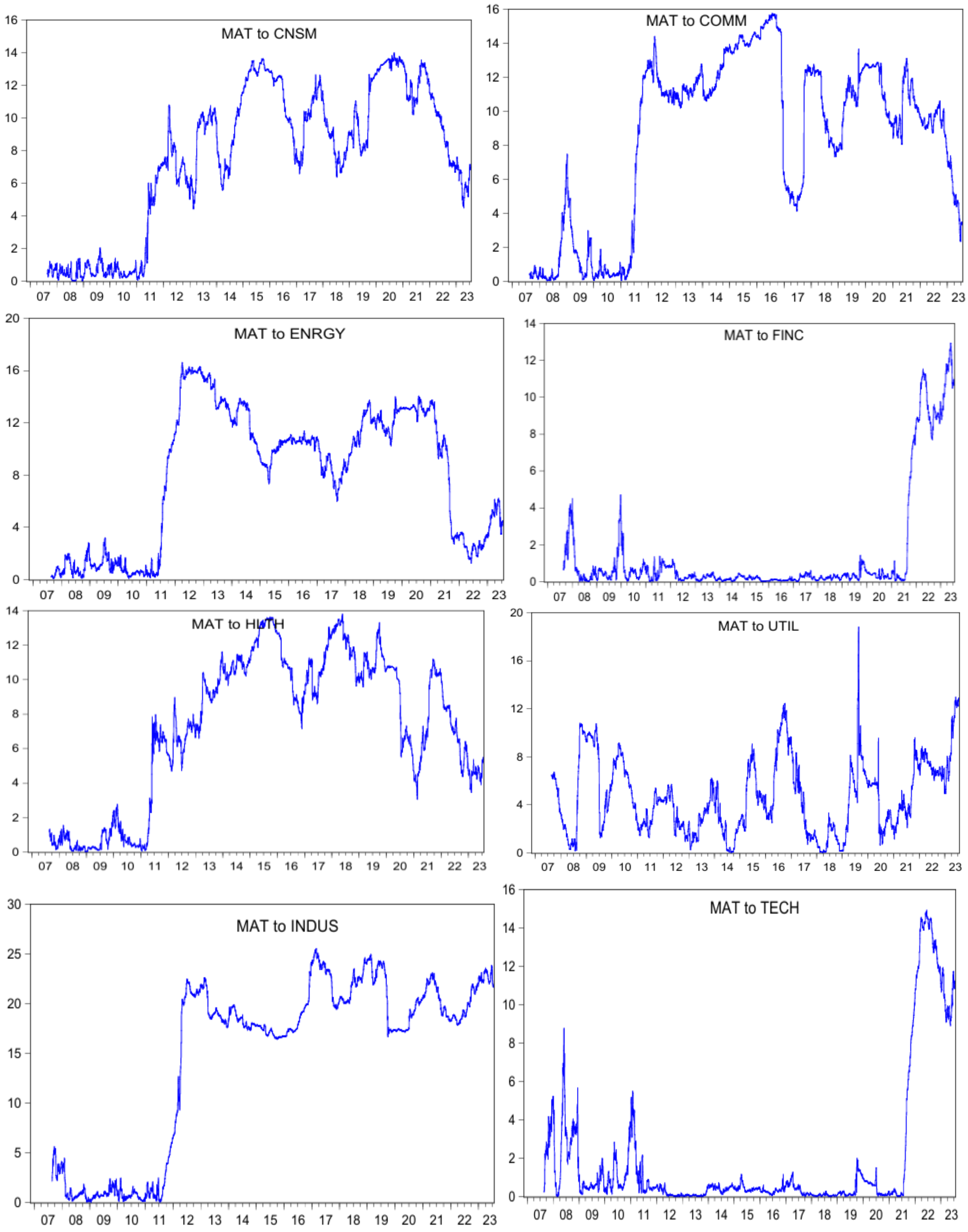
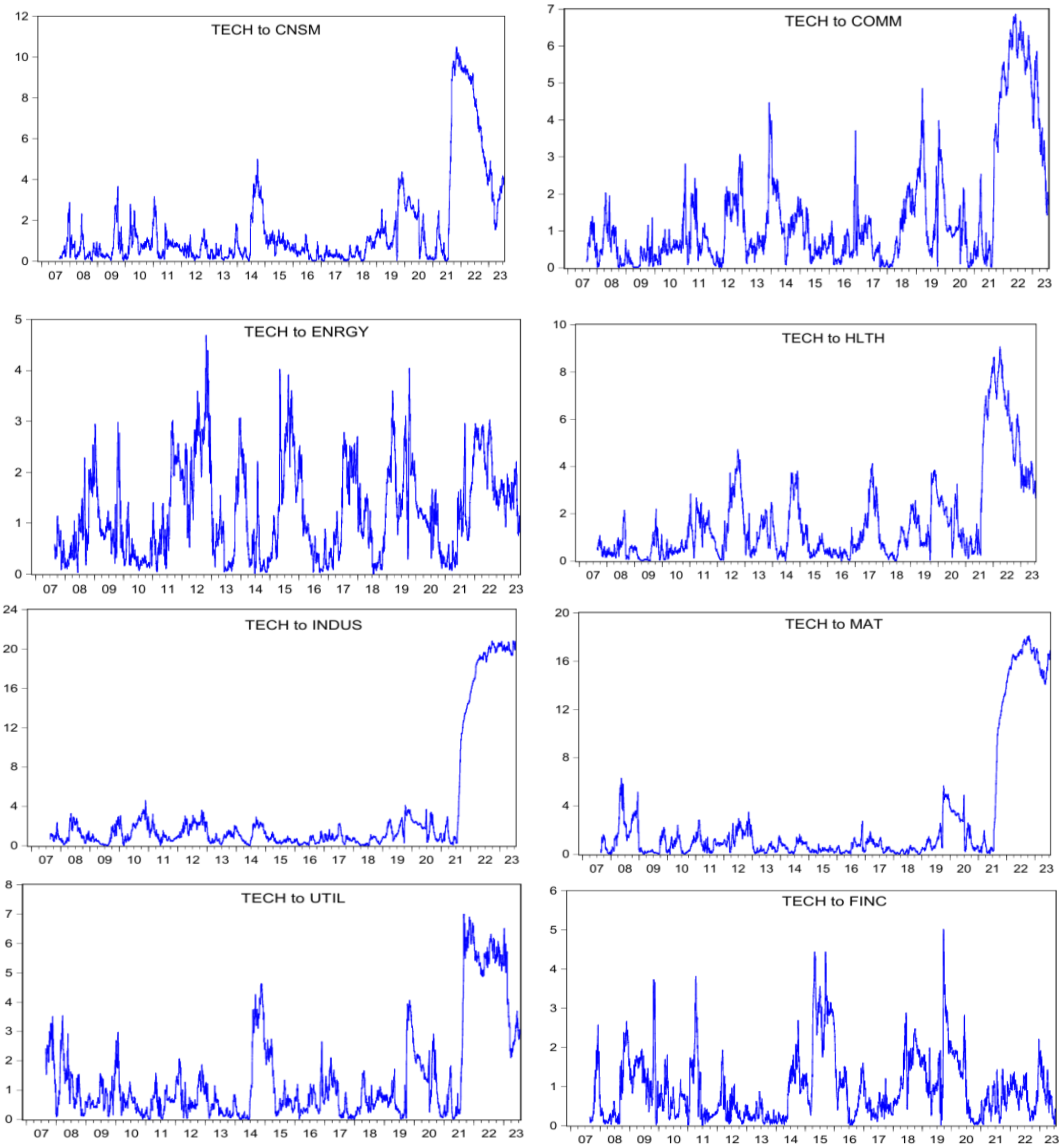
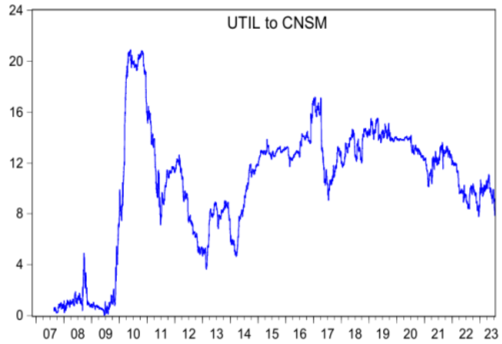
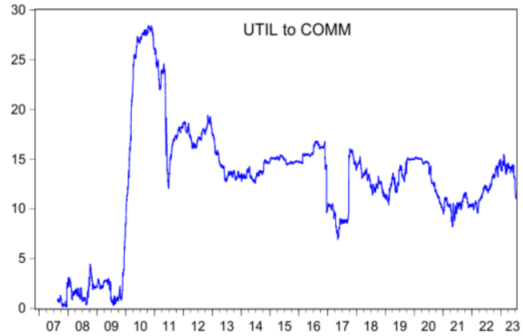
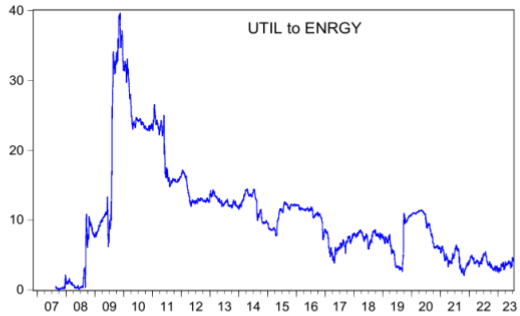
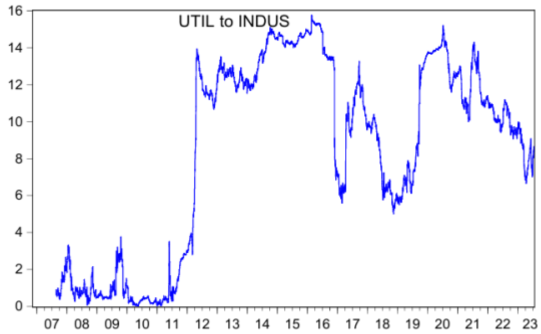
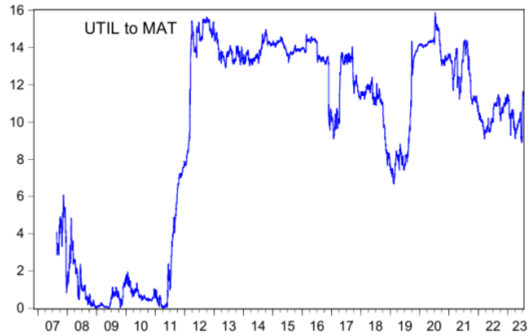
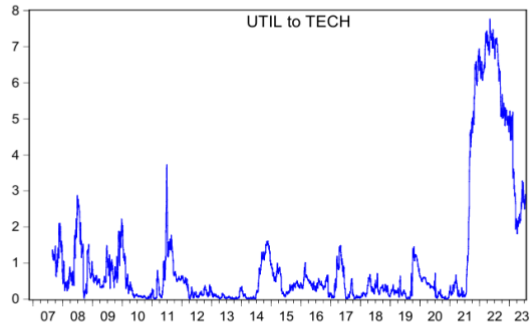
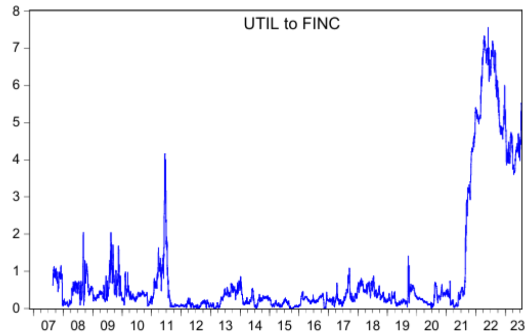
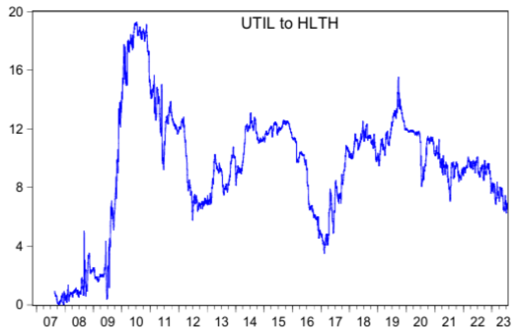
FINC to COMM
FINC to ENRGY
FINC to HLTH
FINC to INDUS
FINC to MAT
FINC to TECH
FINC to UTIL


HLTH to CNSM
HLTH to COMM
HLTH to ENRGY
HLTH to FINC
HLTH to INDUS
HLTH to MAT
HLTH to TECH
HLTH to UTIL

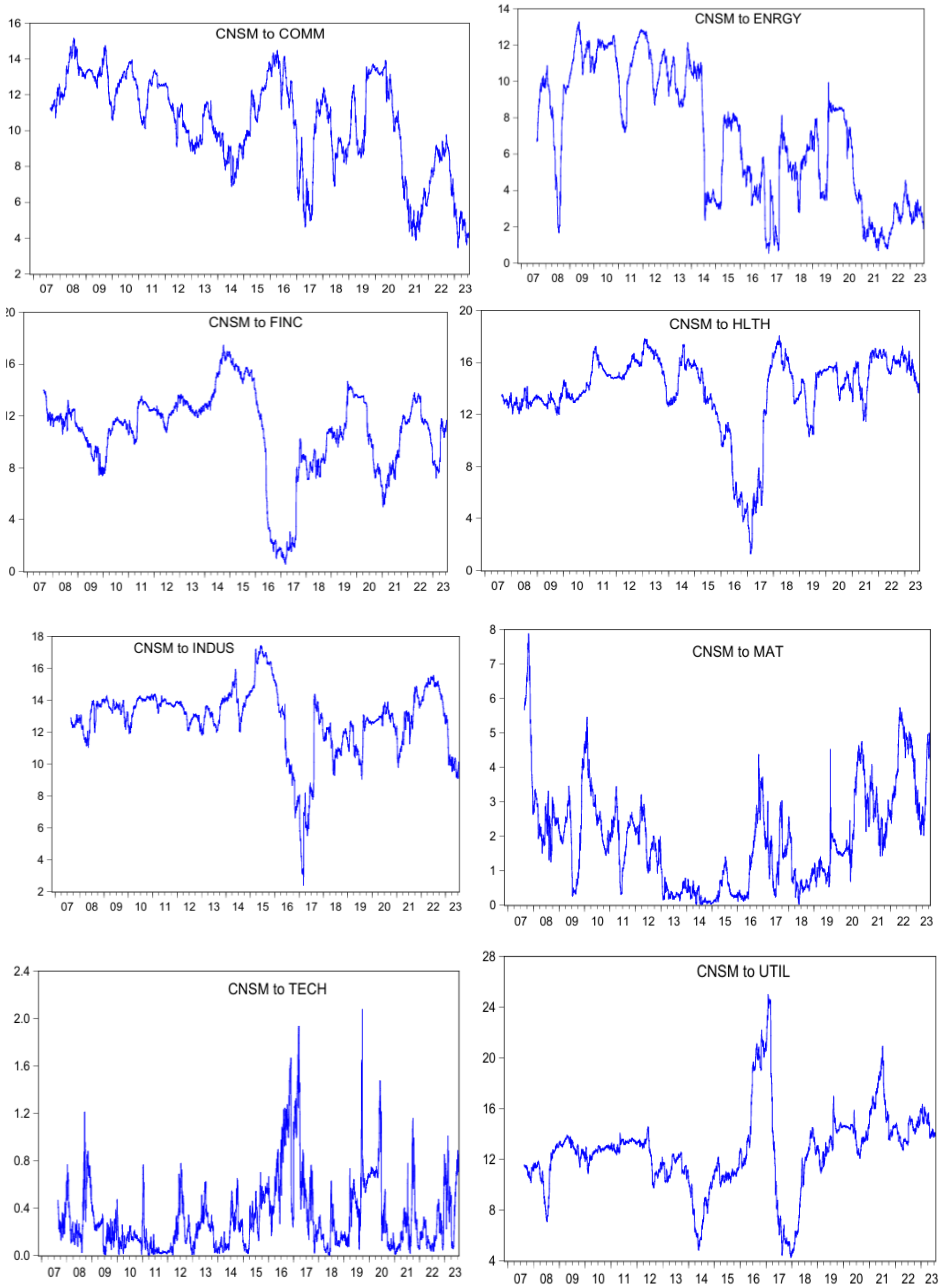

INDUS to CNSM
INDUS to COMM
INDUS to ENRGY
INDUS to FINC
INDUS to HLTH
INDUS to MAT
INDUS to TECH
INDUS to UTIL

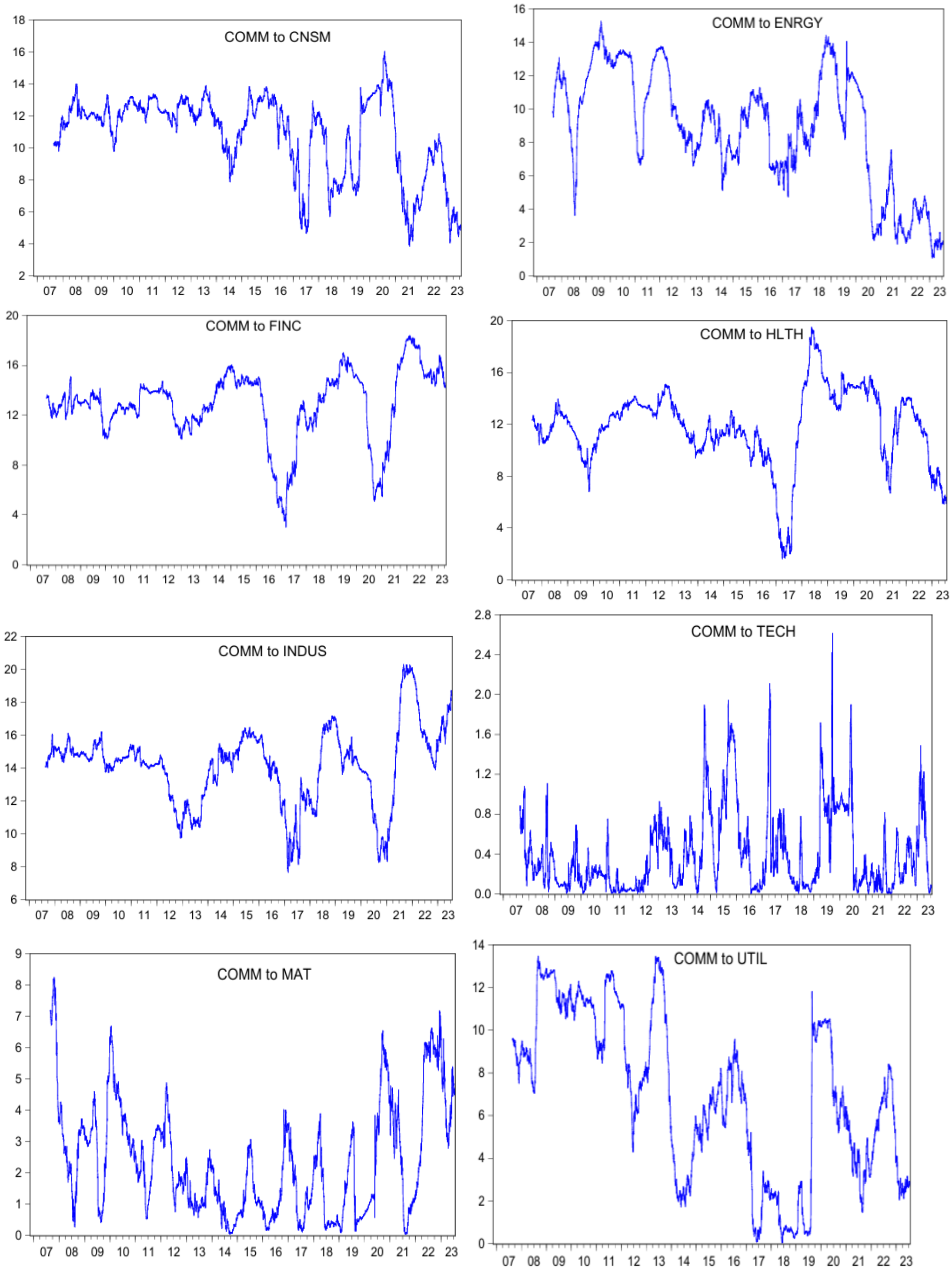

MAT to CNSM
MAT to COMM
MAT to ENRGY
MAT to FINC
MAT to HLTH
MAT to UTIL
MAT to INDUS
MAT to TECH

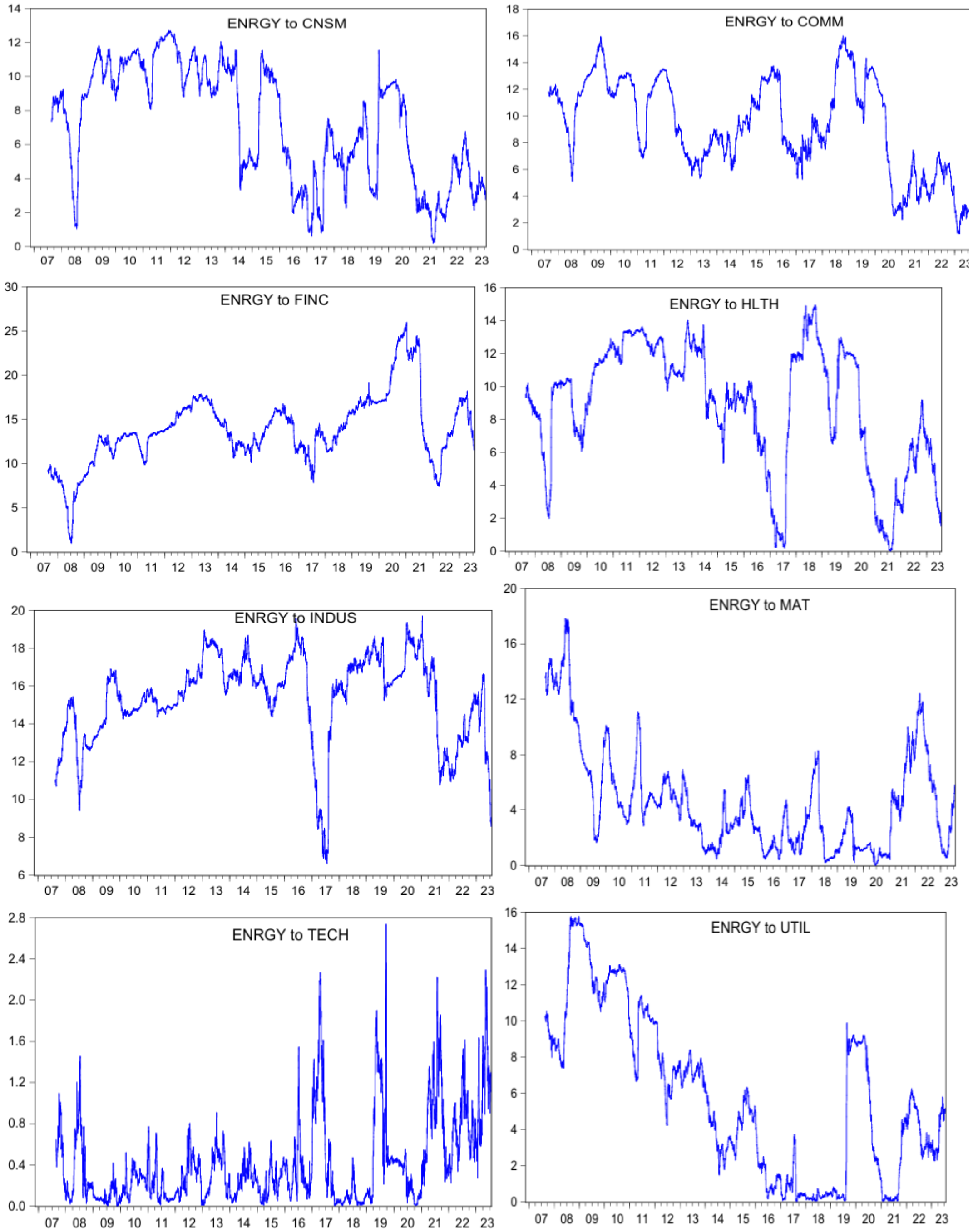

TECH to CNSM
TECH to COMM
TECH to ENRGY
TECH to HLTH
TECH to INDUS
TECH to MAT
TECH to UTIL
TECH to FINC
07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23

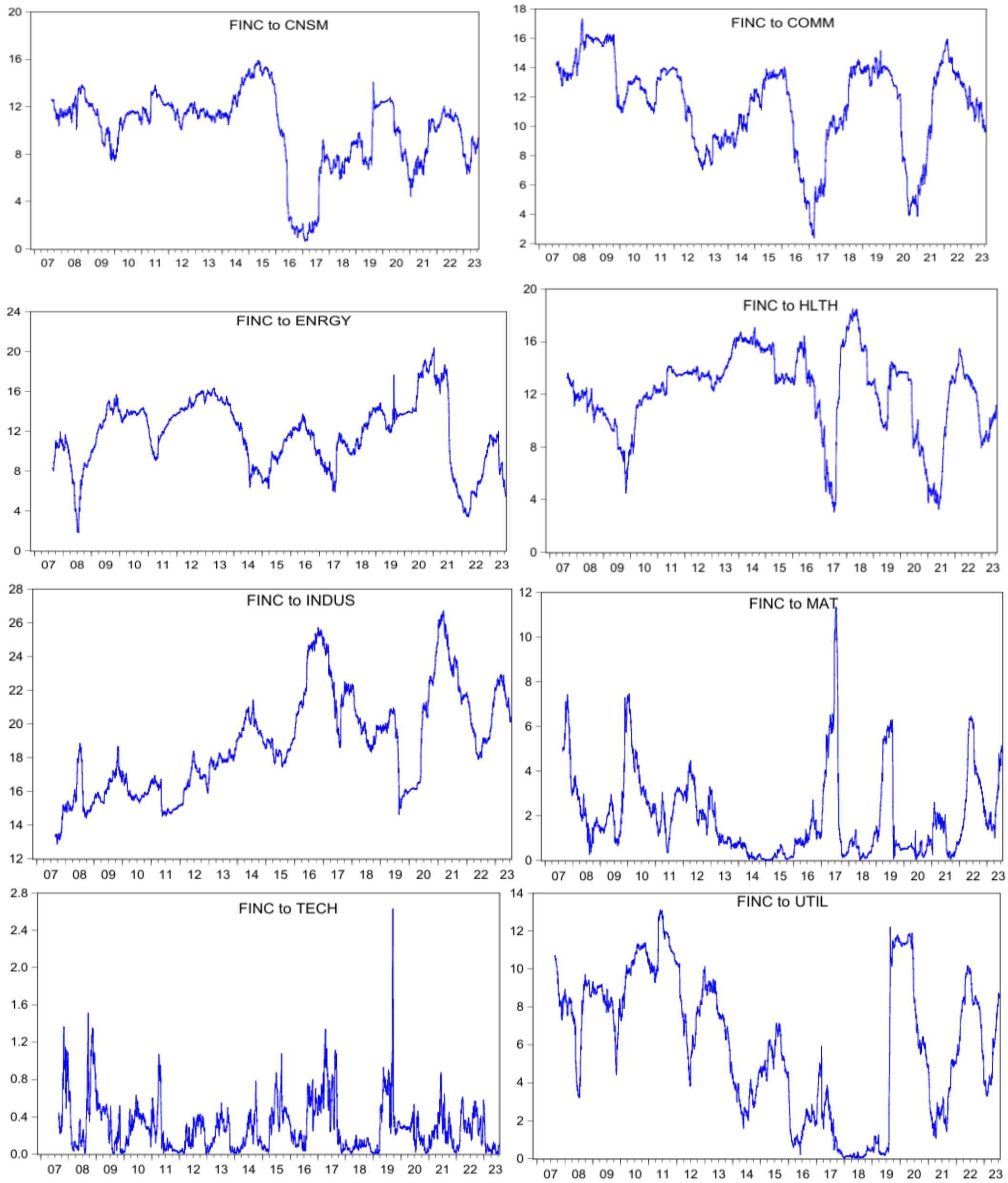

UTIL to CNSM

UTIL to COMM

UTIL to ENRGY

UTIL to INDUS

UTIL to MAT

UTIL to TECH

UTIL to FINC

UTIL to HLTH

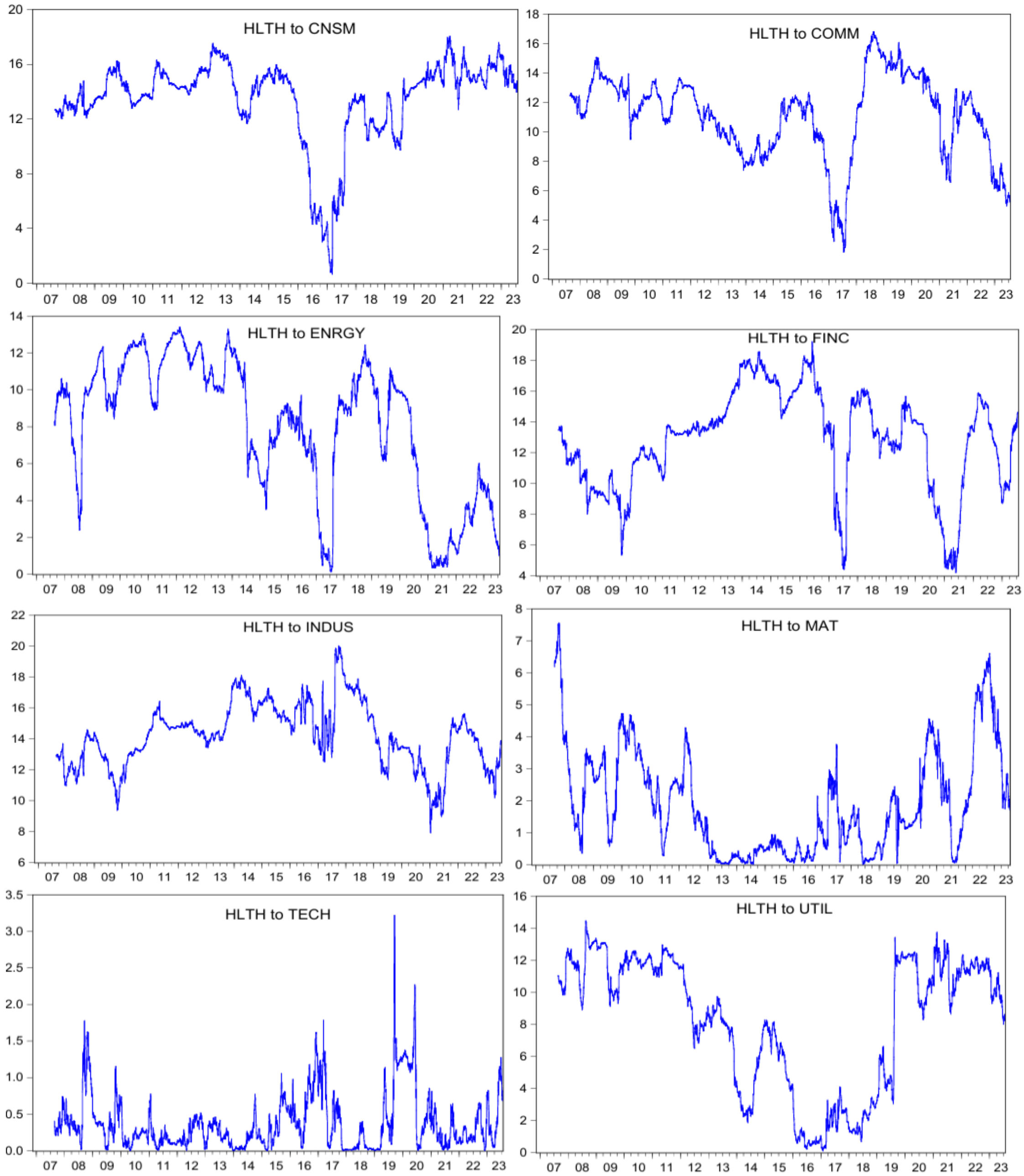
Sample Period 1 – Full Dynamic Connectedness US Sectors

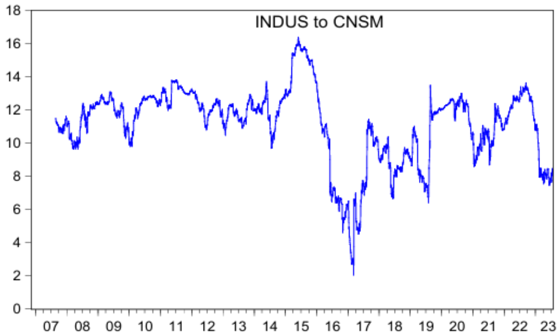


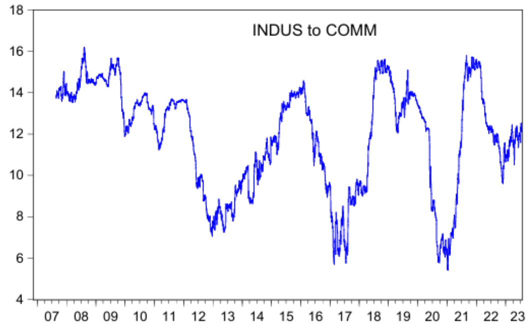

COMM to CNSM
COMM to ENRGY
COMM to FINC
COMM to HLTH
COMM to INDUS
COMM to TECH
COMM to MAT
COMM to UTIL

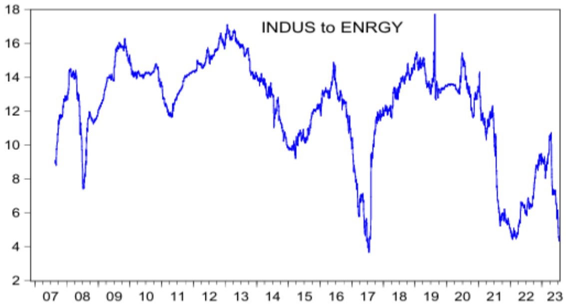

ENRGY to CNSM
ENRGY to COMM
ENRGY to FINC
ENRGY to HLTH
ENRGY to INDUS
ENRGY to MAT
ENRGY to TECH
ENRGY to UTIL

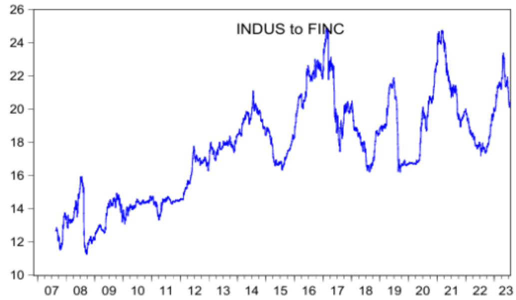

FINC to CNSM
FINC to COMM
FINC to ENRGY
FINC to HLTH
FINC to INDUS
FINC to MAT
FINC to TECH
FINC to UTIL


HLTH to CNSM
HLTH to COMM
HLTH to ENRGY
HLTH to FINC
HLTH to INDUS
HLTH to MAT
HLTH to TECH
HLTH to UTIL

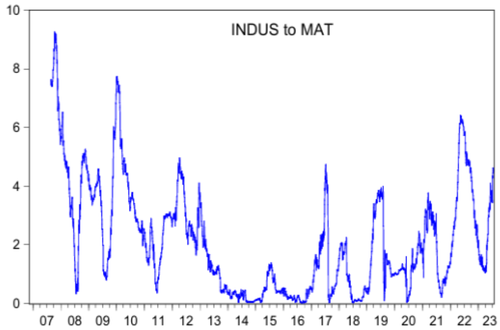

INDUS to CNSM

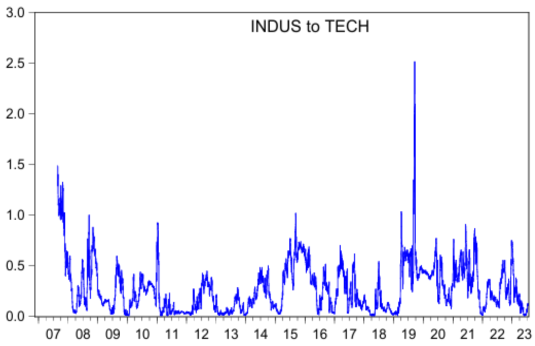

INDUS to COMM

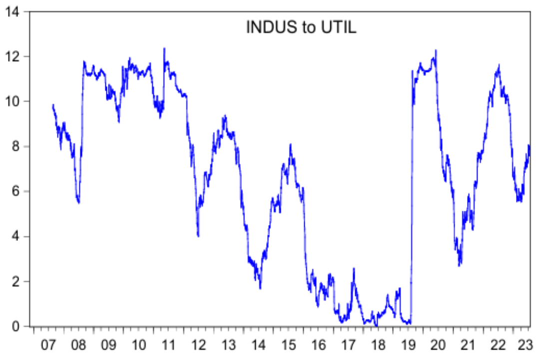

INDUS to ENRGY

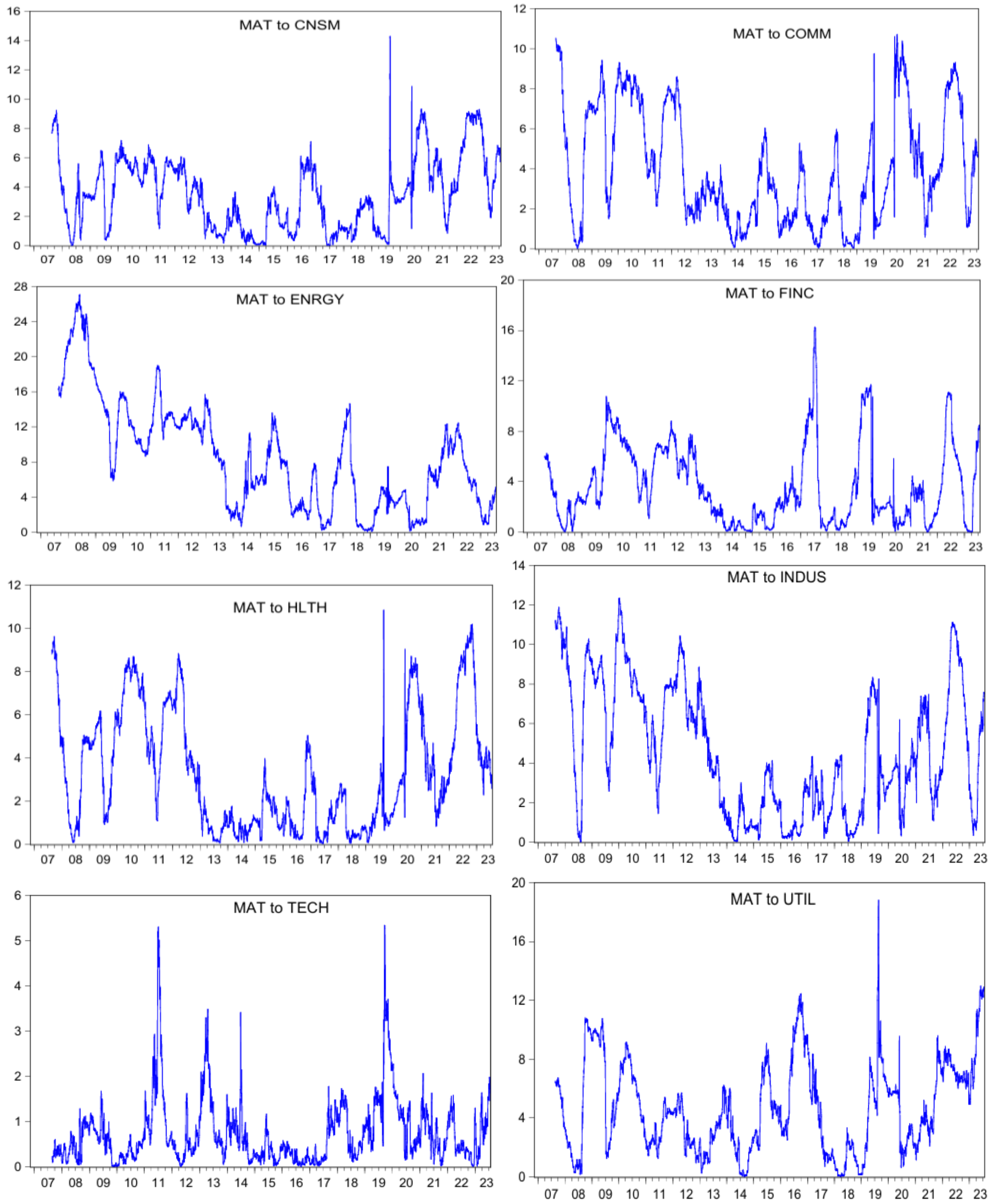

INDUS to FINC

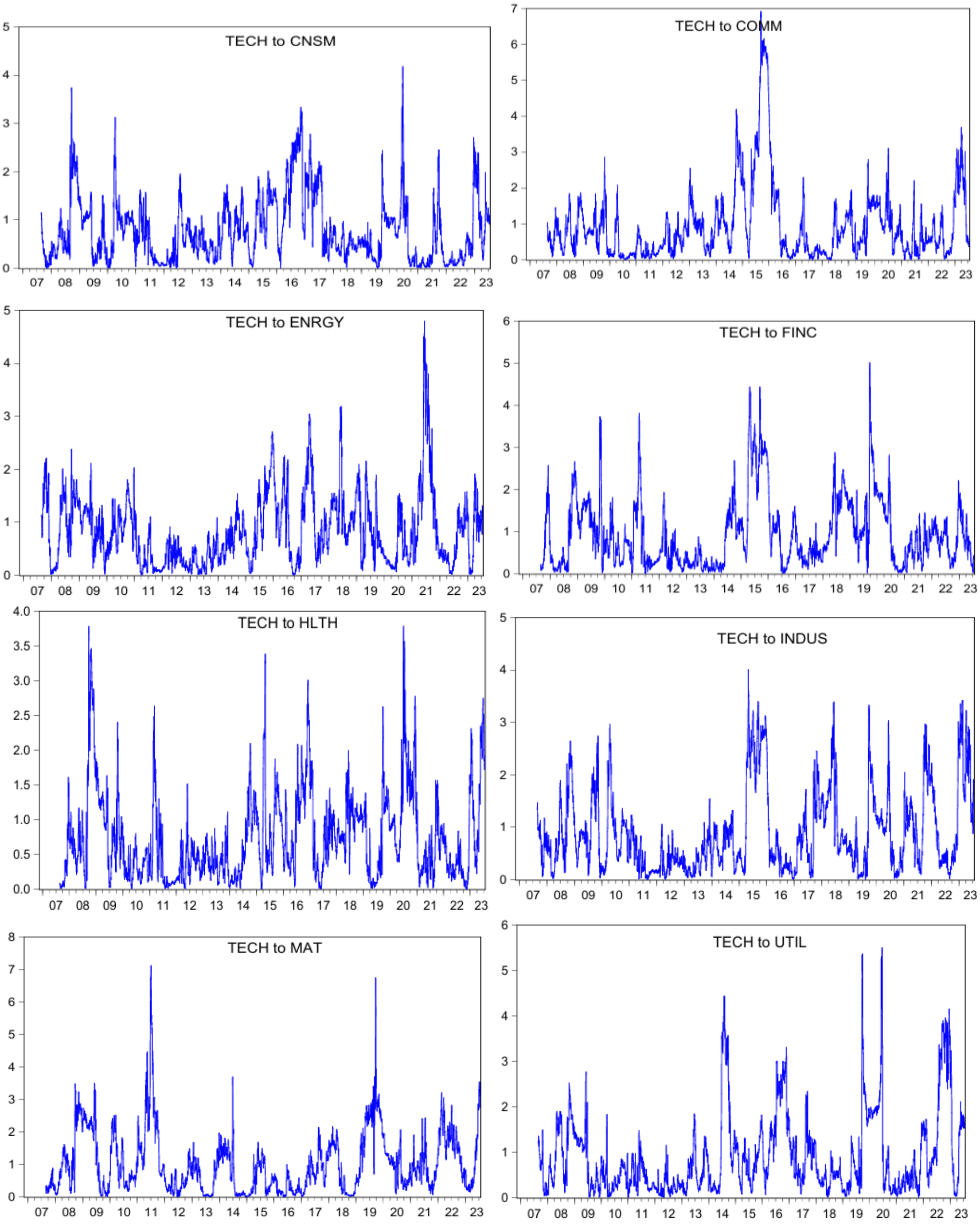

INDUS to HLTH

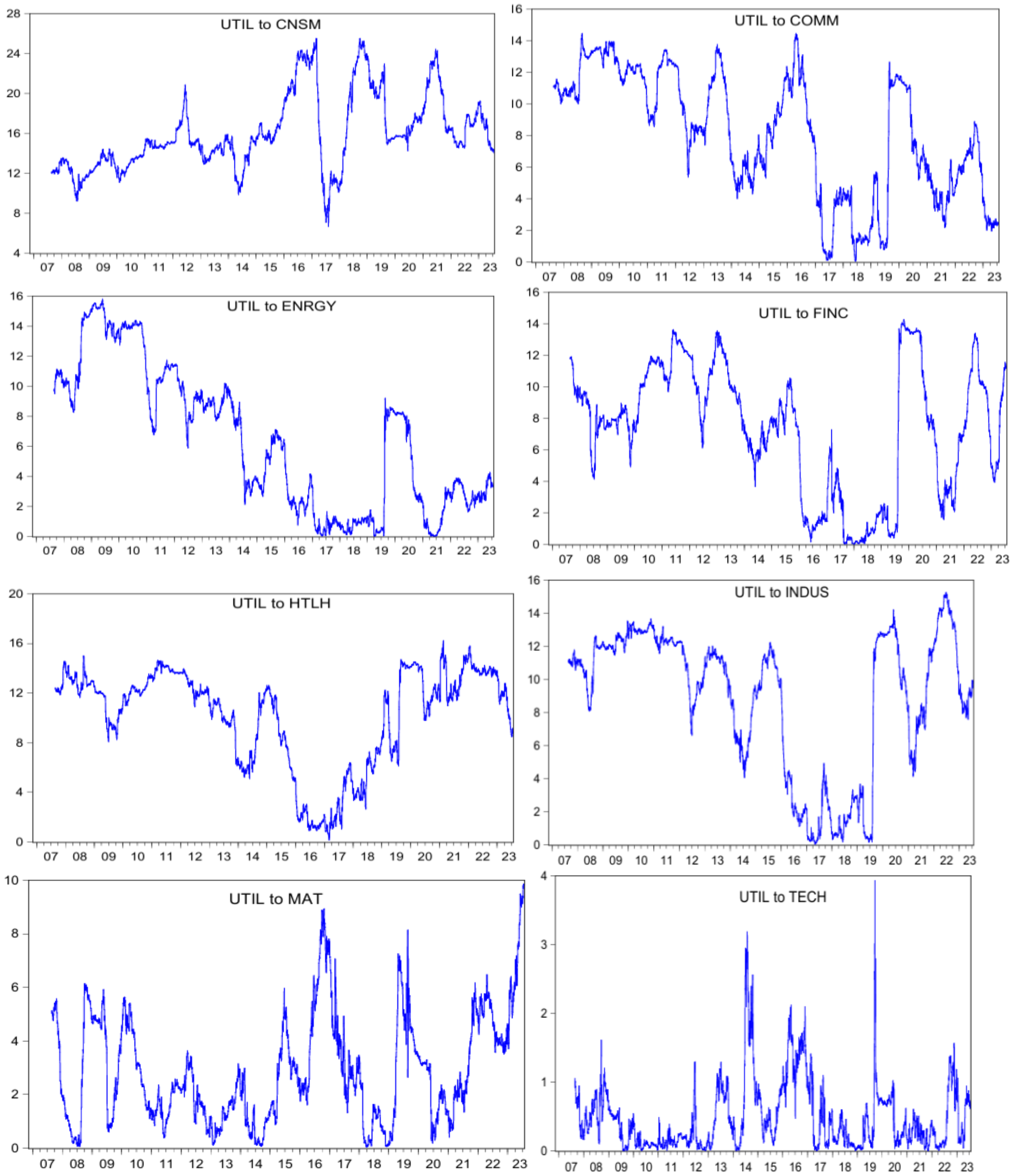

INDUS to MAT


INDUS to TECH

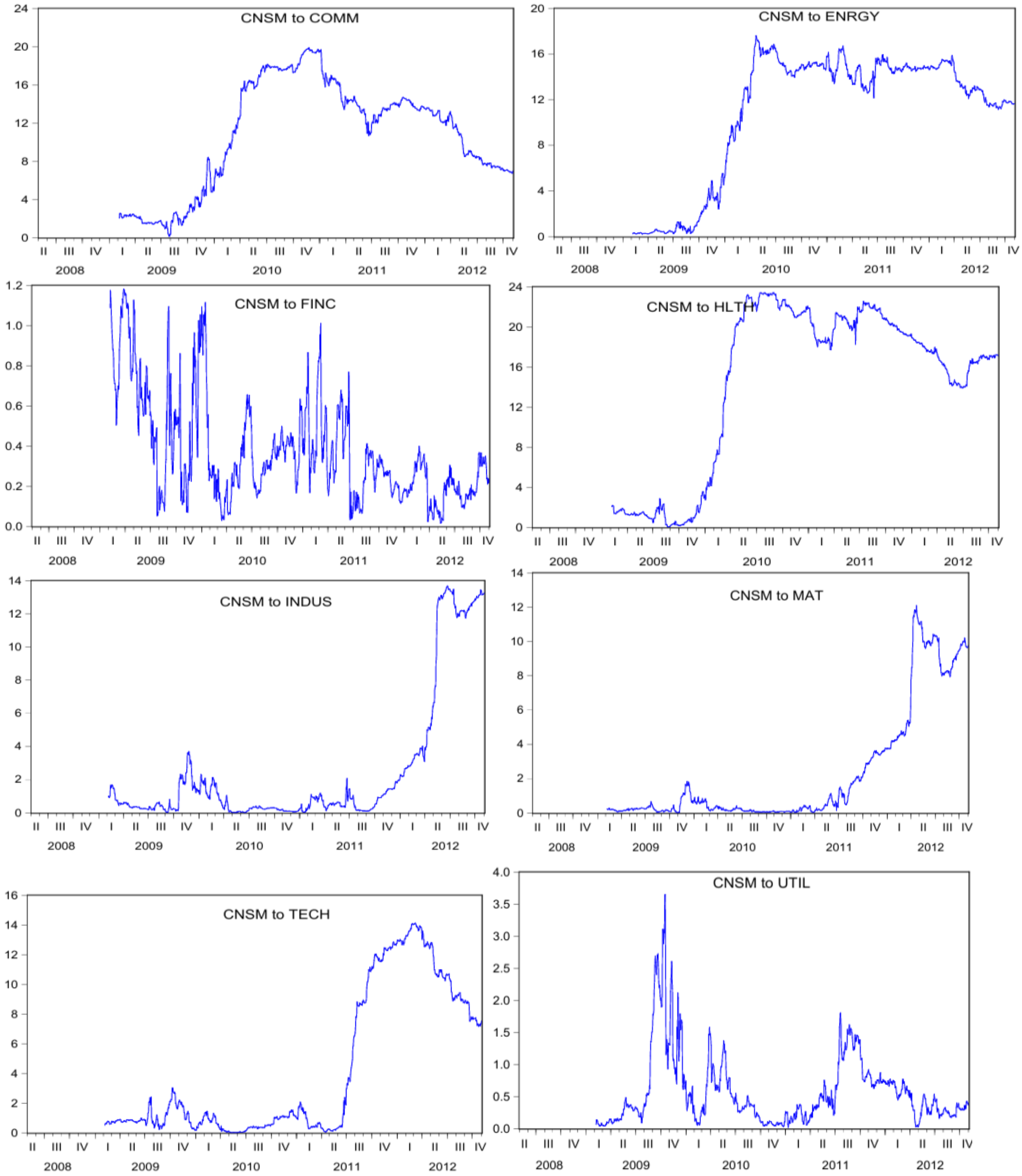

INDUS to UTIL

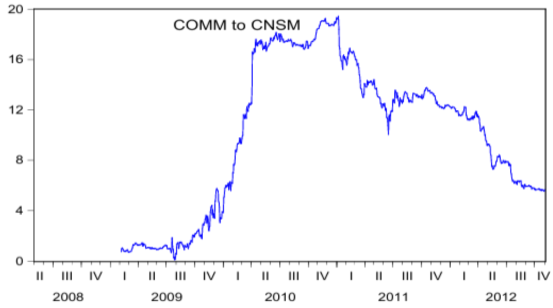

MAT to CNSM
MAT to COMM
MAT to ENRGY
MAT to FINC
MAT to HLTH
MAT to INDUS
MAT to TECH
MAT to UTIL

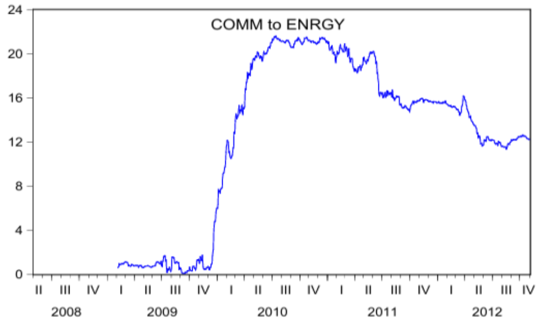

TECH to CNSM
TECH to COMM
TECH to ENRGY
TECH to FINC
TECH to HLTH
TECH to INDUS
TECH to MAT
TECH to UTIL
07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23

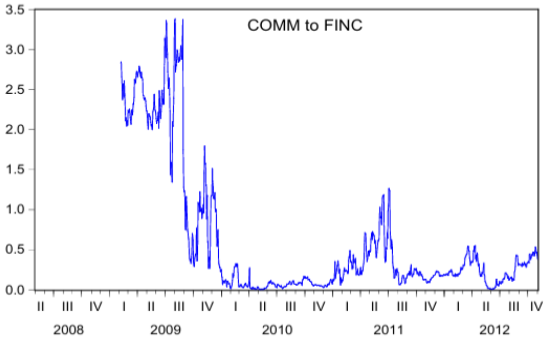

UTIL to CNSM
UTIL to COMM
UTIL to ENRGY
UTIL to FINC
UTIL to HTLH
UTIL to INDUS
UTIL to MAT
UTIL to TECH
07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23

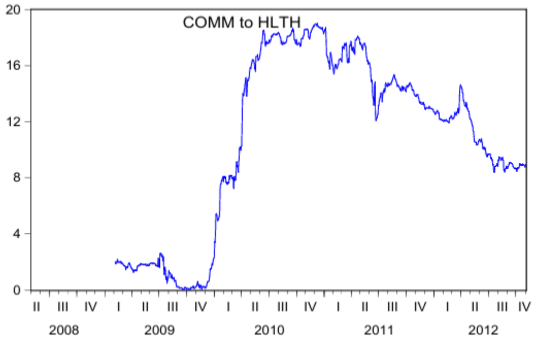
Sample Period 2 – Financial Crisis Dynamic Connectedness EU Sectors

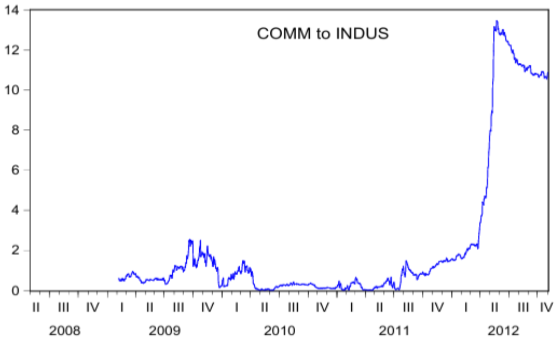


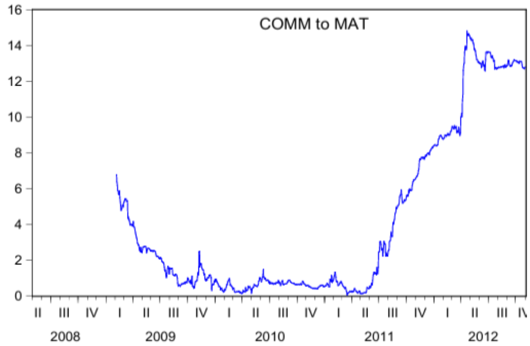

COMM to CNSM
0
4
8
12
16
20
2008
2009
2010
2011
2012

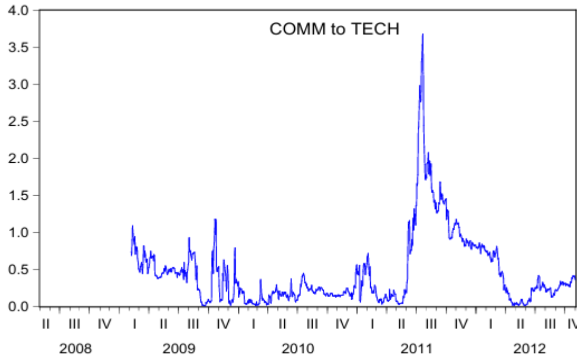

COMM to ENRGY
0
4
8
12
16
20
24
2008
2009
2010
2011
2012

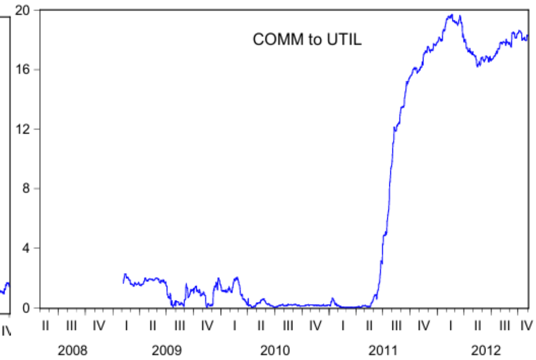

COMM to FINC
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2008
2009
2010
2011
2012

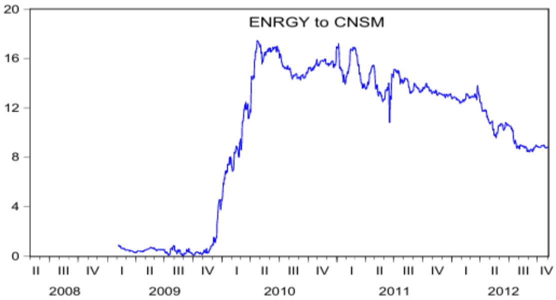

COMM to HLTH
0
4
8
12
16
20
2008
2009
2010
2011
2012

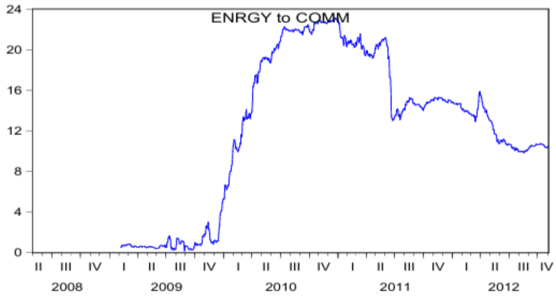

COMM to INDUS
0
2
4
6
8
10
12
14
2008
2009
2010
2011
2012

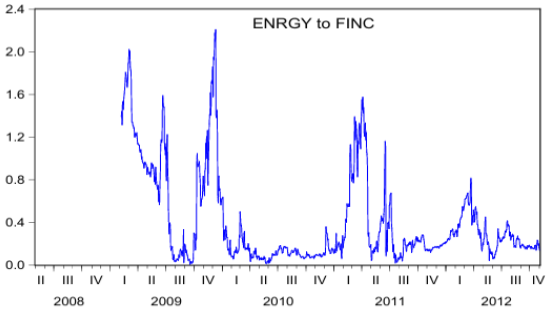

COMM to MAT
0
2
4
6
8
10
12
14
16
2008
2009
2010
2011
2012

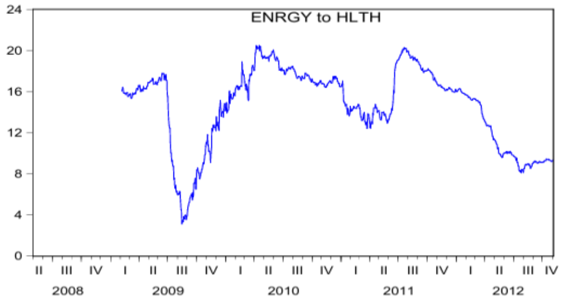

COMM to TECH
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
2008
2009
2010
2011
2012

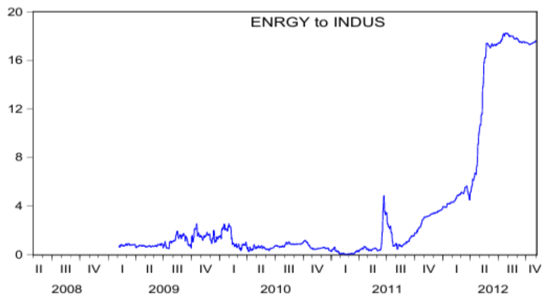

COMM to UTIL
0
4
8
12
16
20
2008
2009
2010
2011
2012

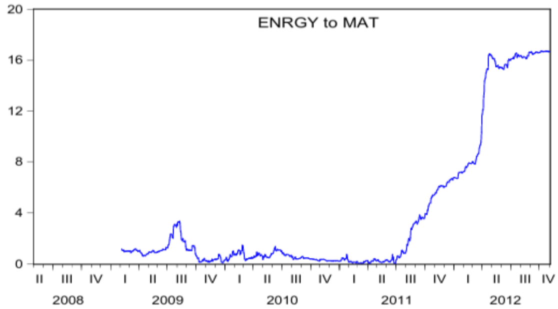

ENRGY to CNSM
20
16
12
8
4
0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

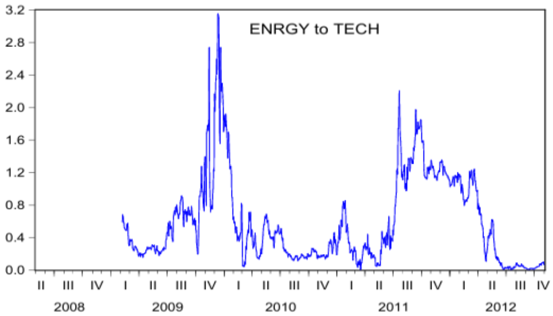

ENRGY to COMM
24
20
16
12
8
4
0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

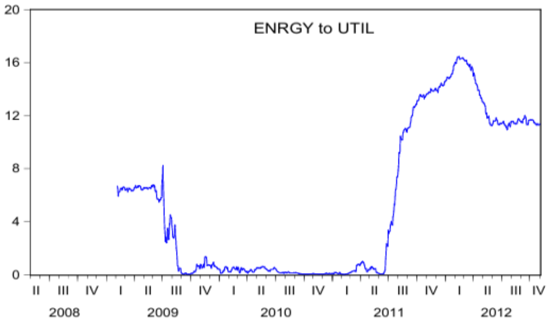

ENRGY to FINC
2.4
2.0
1.6
1.2
0.8
0.4
0.0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

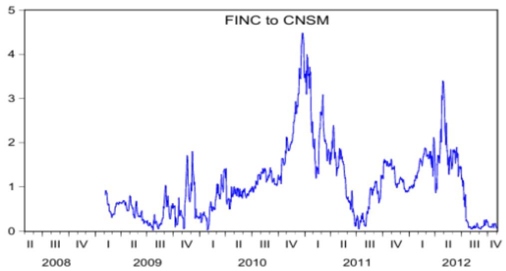

ENRGY to HLTH
24
20
16
12
8
4
0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

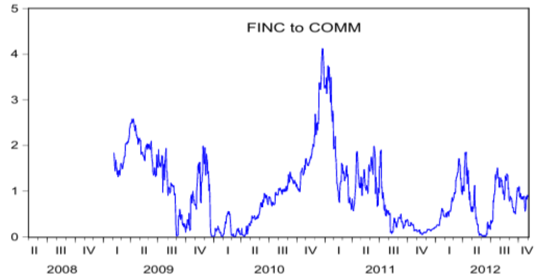

ENRGY to INDUS
20
16
12
8
4
0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

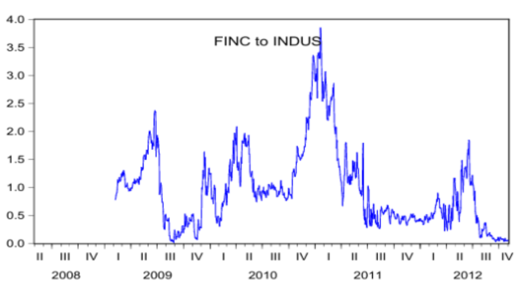

ENRGY to MAT
20
16
12
8
4
0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

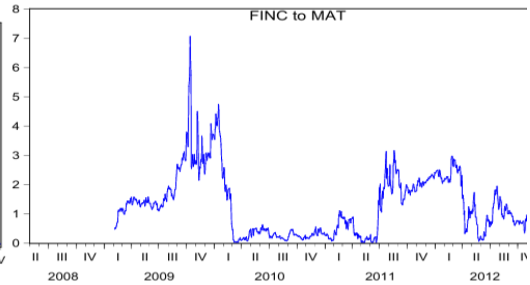

ENRGY to TECH
3.2
2.8
2.4
2.0
1.6
1.2
0.8
0.4
0.0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

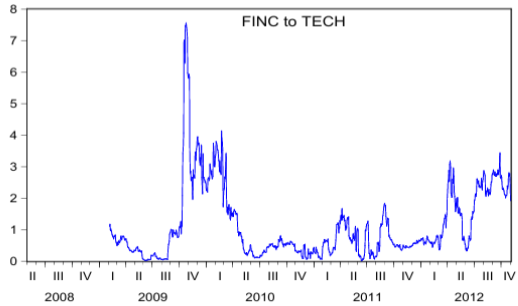

ENRGY to UTIL
20
16
12
8
4
0
II III IV I II III IV I II III IV I II III IV I II III IV
2008
2009
2010
2011
2012

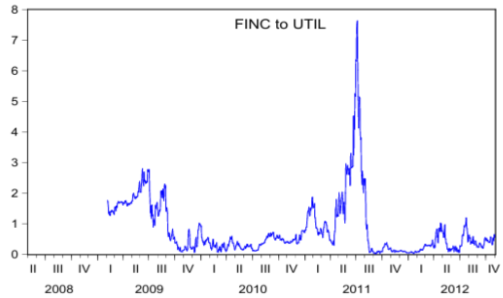

FINC to CNSM
2008
2009
2010
2011
2012

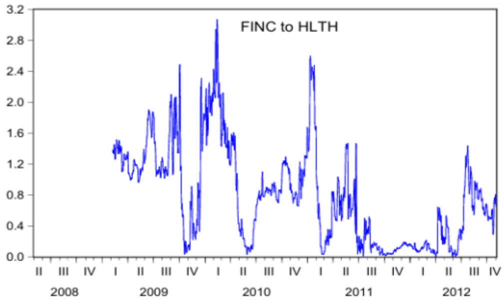

FINC to COMM
2008
2009
2010
2011
2012

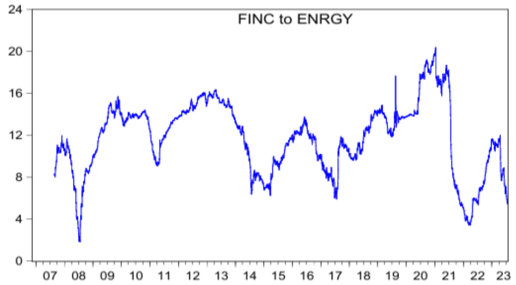

FINC to INDUS
2008
2009
2010
2011
2012

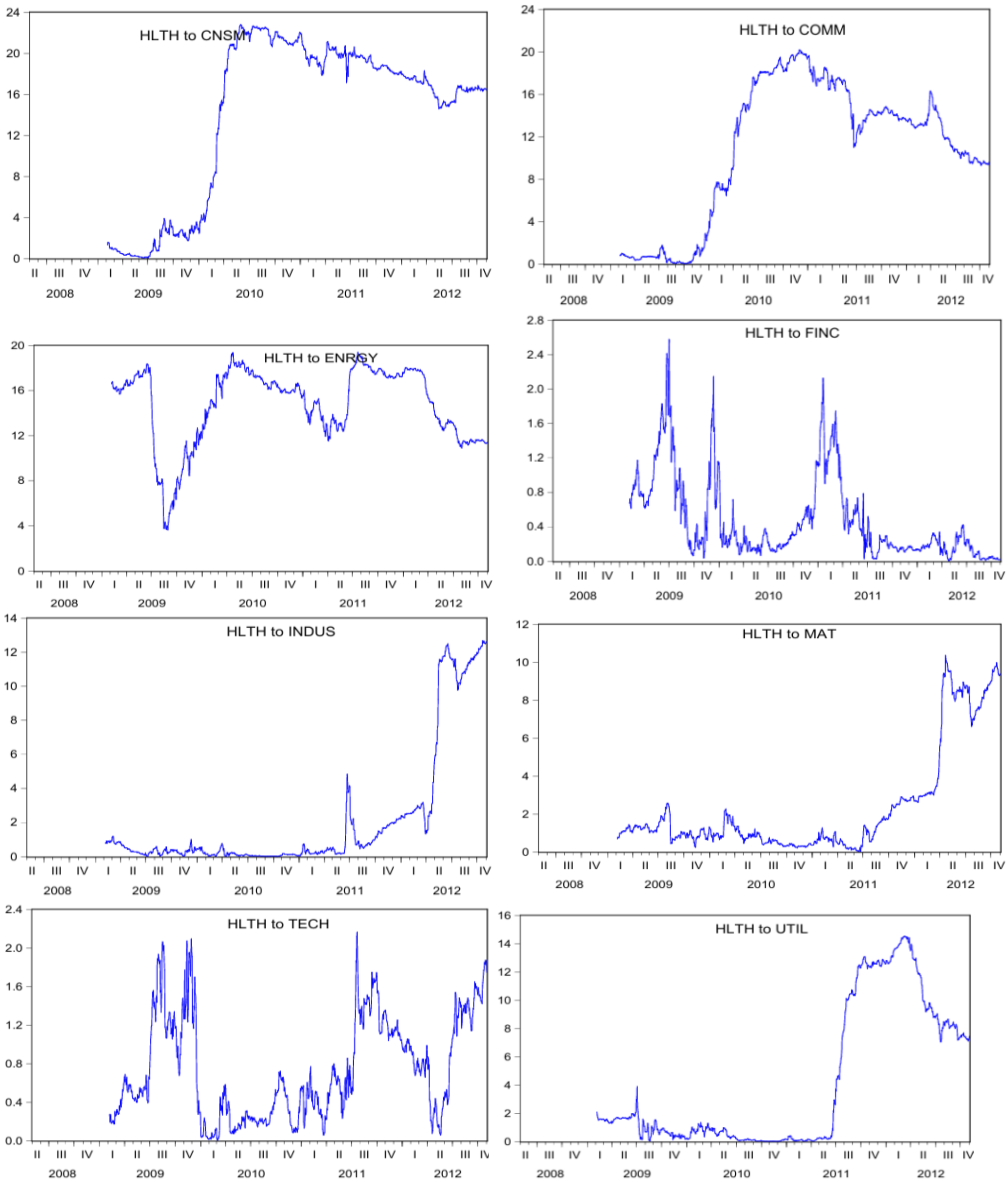

FINC to MAT
2008
2009
2010
2011
2012

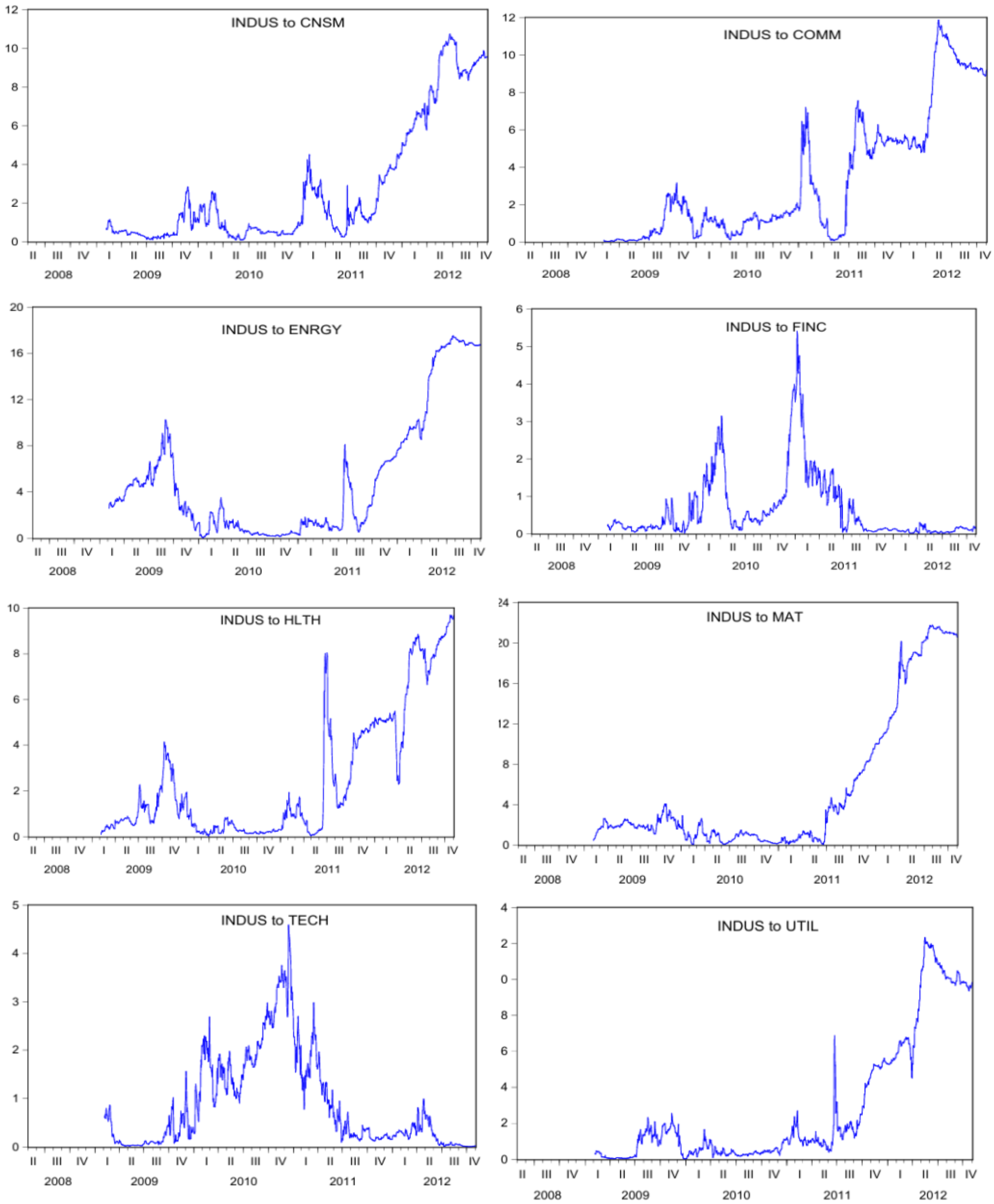

FINC to TECH
2008
2009
2010
2011
2012

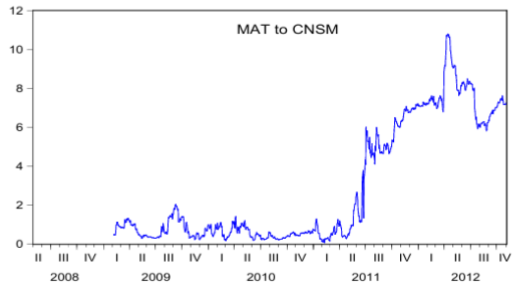

FINC to UTIL
2008
2009
2010
2011
2012

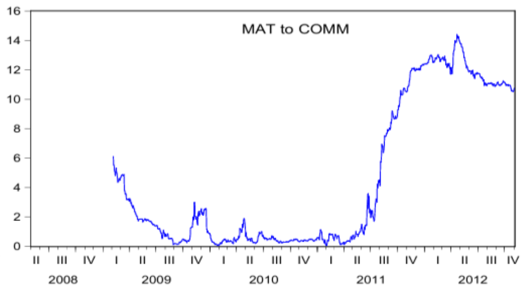

FINC to HLTH
2008
2009
2010
2011
2012

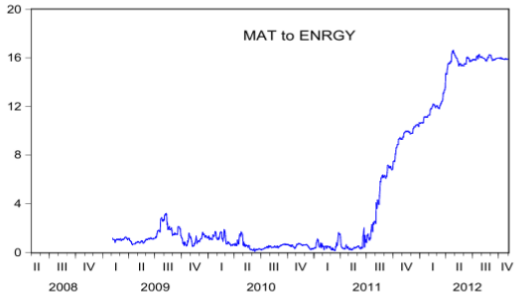

FINC to ENRGY
07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23

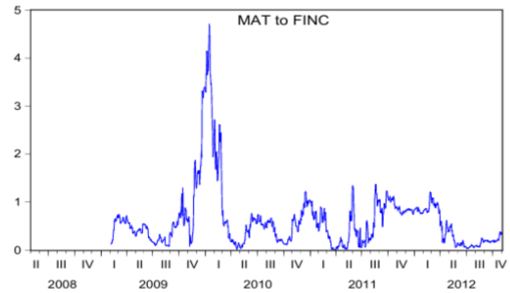

HLTH to CNSM
HLTH to COMM
HLTH to ENRGY
HLTH to FINC
HLTH to INDUS
HLTH to MAT
HLTH to TECH
HLTH to UTIL

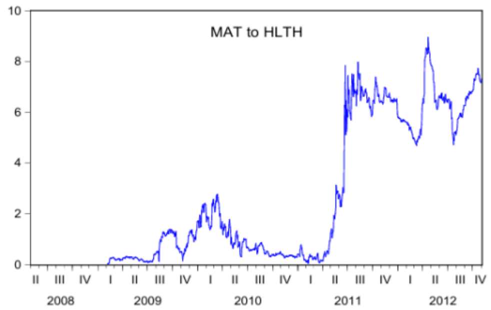

INDUS to CNSM
INDUS to COMM
INDUS to ENRGY
INDUS to FINC
INDUS to HLTH
INDUS to MAT
INDUS to TECH
INDUS to UTIL
2008
2009
2010
2011
2012

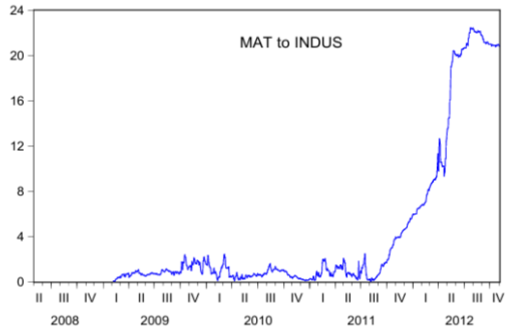

MAT to CNSM

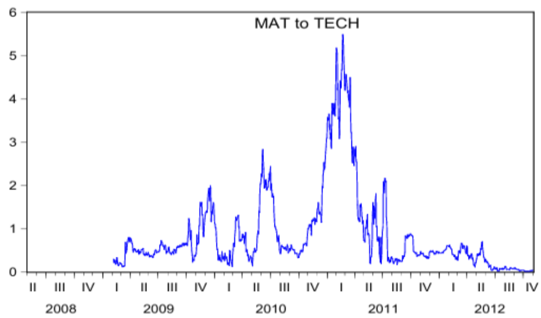

MAT to COMM

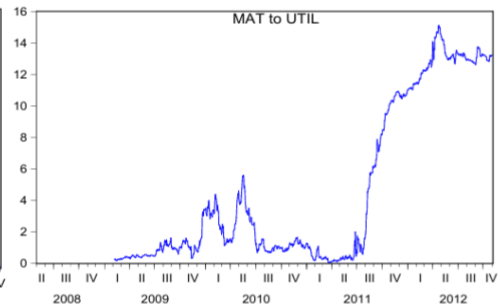

MAT to ENRGY

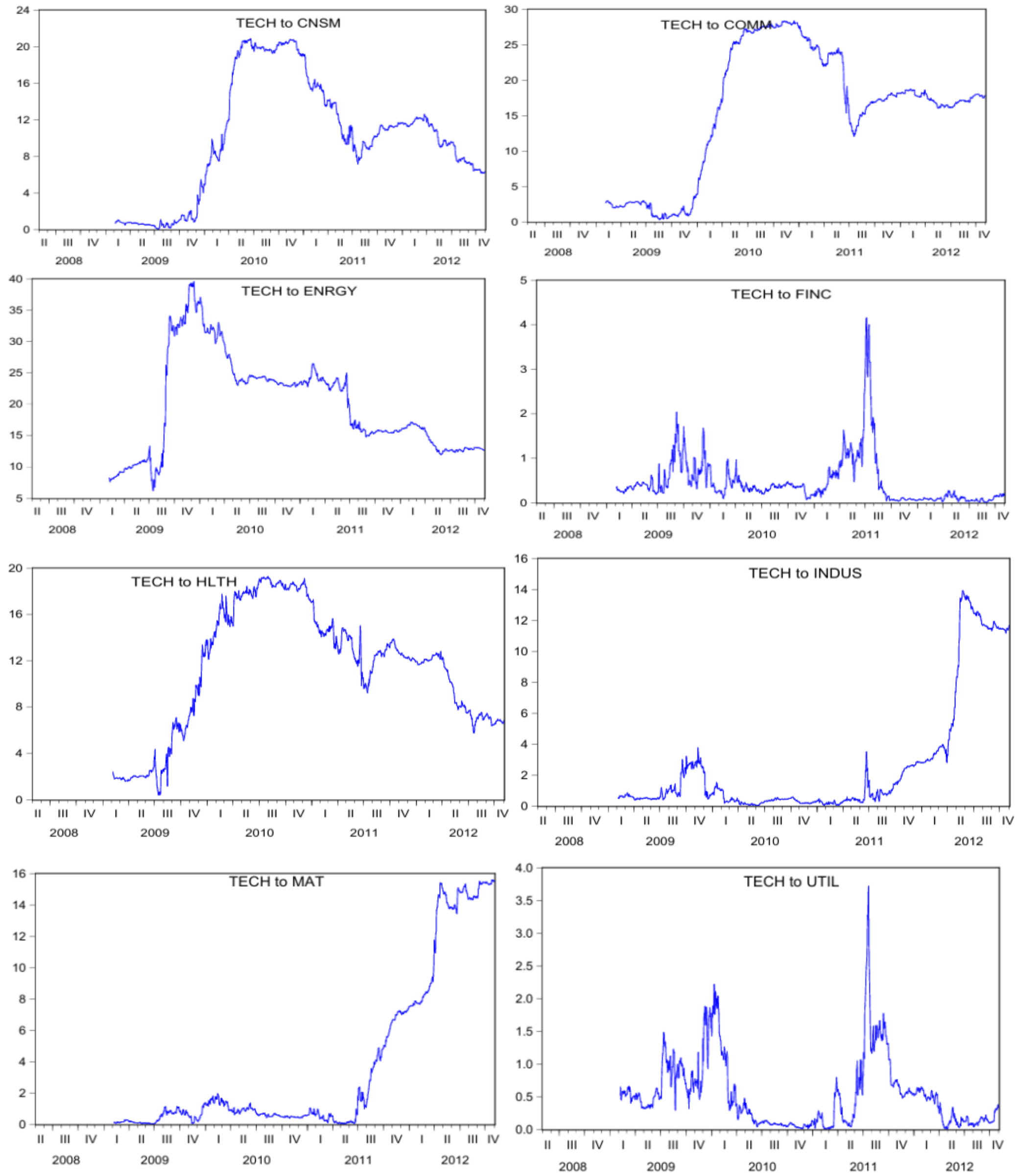

MAT to FINC

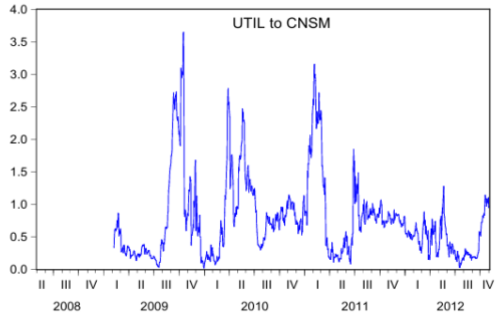

MAT to HLTH

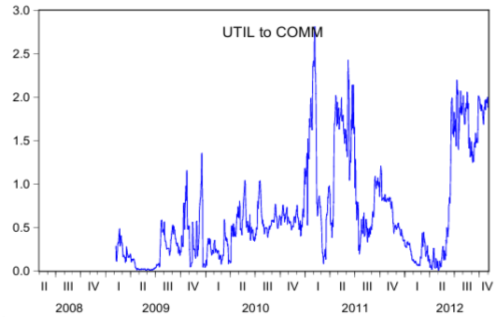

MAT to INDUS

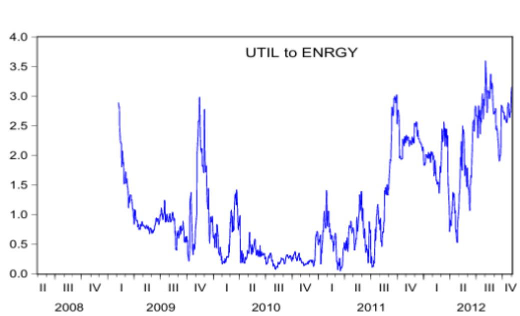

MAT to TECH

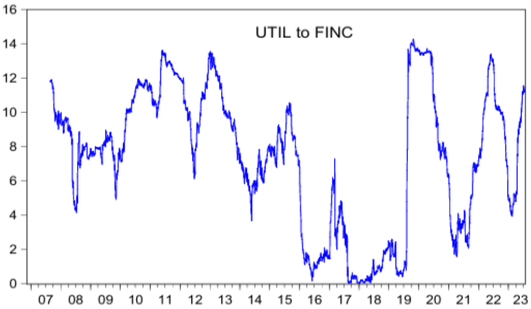

MAT to UTIL

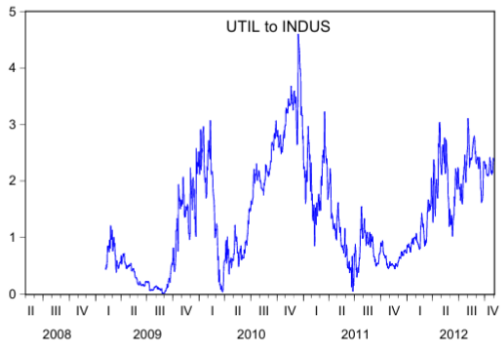

TECH to CNSM
TECH to COMM
TECH to ENRGY
TECH to FINC
TECH to HLTH
TECH to INDUS
TECH to MAT
TECH to UTIL
2008
2009
2010
2011
2012

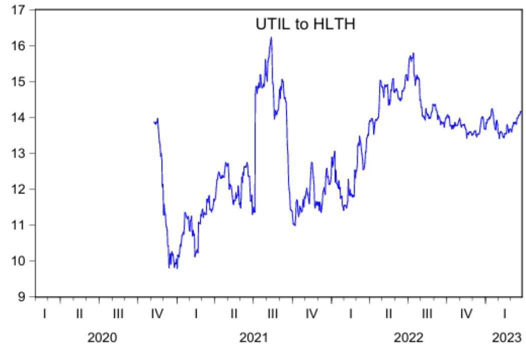

UTIL to CNSM
2008
2009
2010
2011
2012

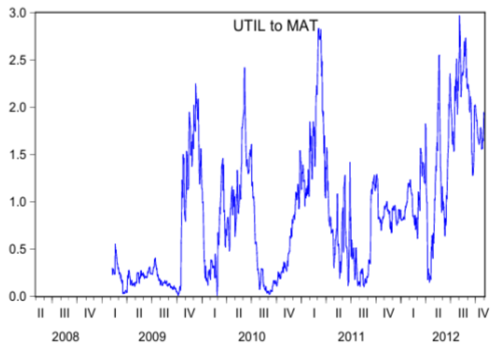

UTIL to COMM
2008
2009
2010
2011
2012

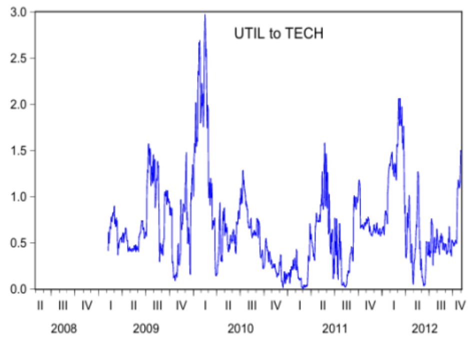

UTIL to ENRGY
2008
2009
2010
2011
2012


UTIL to FINC
07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23

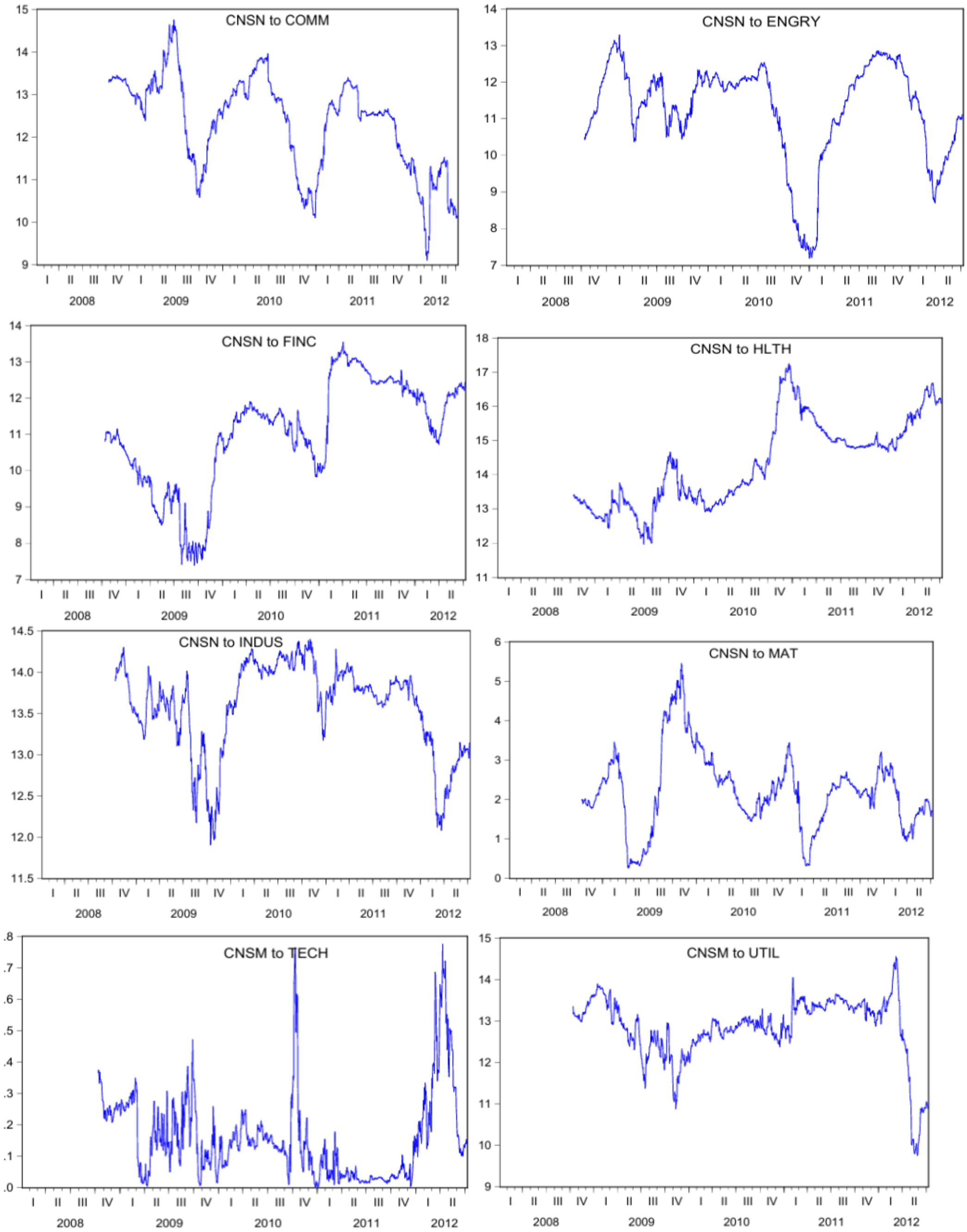

UTIL to INDUS
2008
2009
2010
2011
2012


UTIL to HLTH
2020
2021
2022
2023

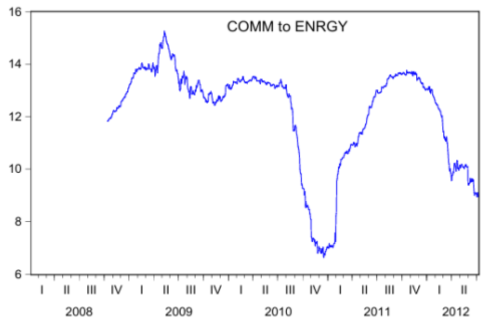

UTIL to MAT
2008
2009
2010
2011
2012

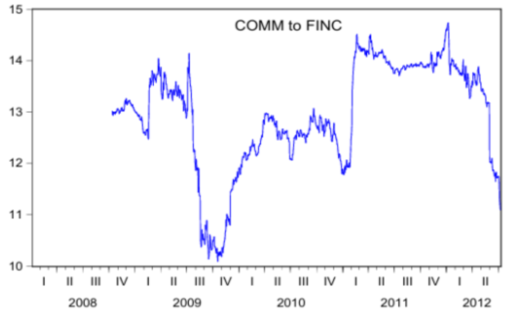

UTIL to TECH
2008
2009
2010
2011
2012

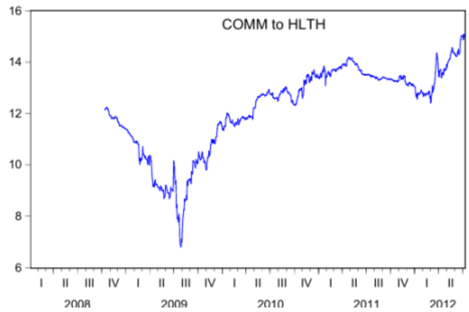
Sample Period 2 – Financial Crisis Dynamic Connectedness US Sectors



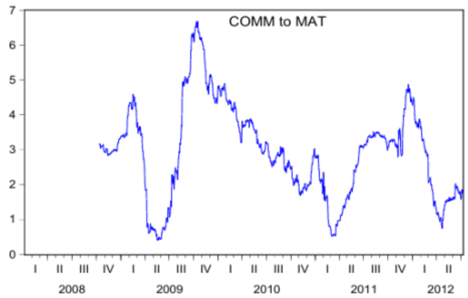

COMM to CNSM
13.5
13.0
12.5
12.0
11.5
11.0
10.5
10.0
9.5
2008
2009
2010
2011
2012

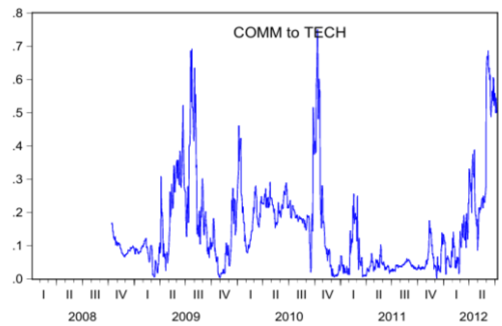

COMM to ENRGY
16
14
12
10
8
6
2008
2009
2010
2011
2012

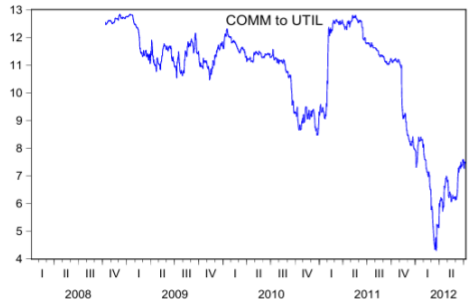

COMM to FINC
15
14
13
12
11
10
2008
2009
2010
2011
2012

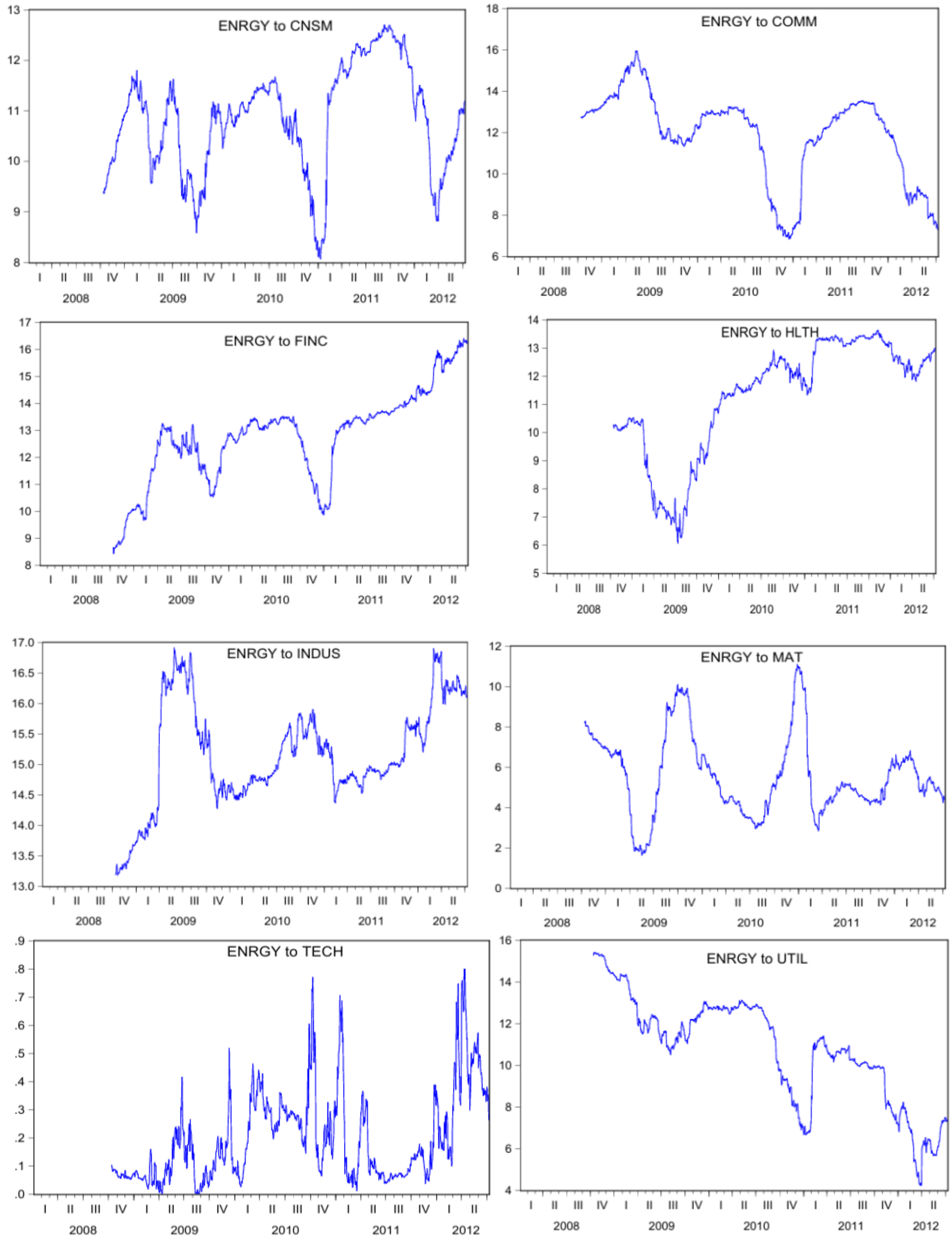

COMM to HLTH
16
14
12
10
8
6
2008
2009
2010
2011
2012

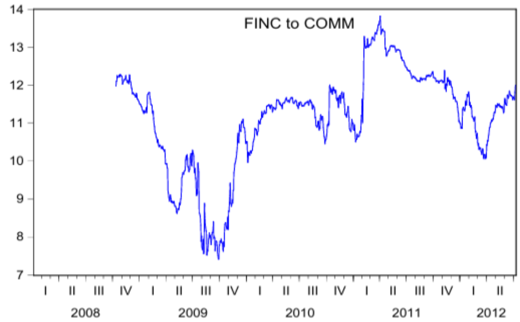

COMM to INDUS
17
16
15
14
13
12
11
10
2008
2009
2010
2011
2012

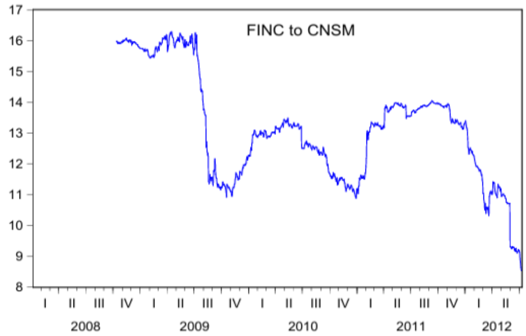

COMM to MAT
7
6
5
4
3
2
1
0
2008
2009
2010
2011
2012

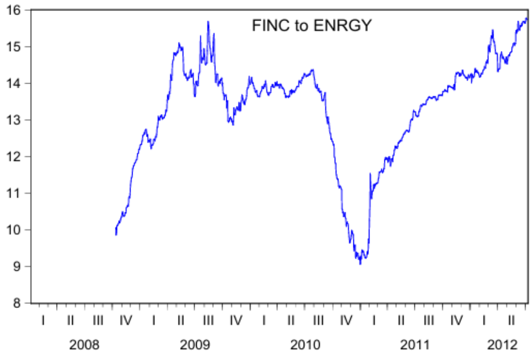

COMM to TECH
.8
.7
.6
.5
.4
.3
.2
.1
.0
2008
2009
2010
2011
2012

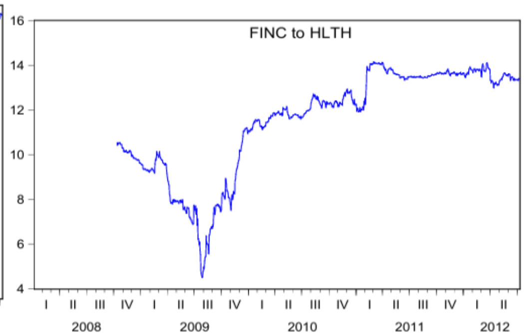

COMM to UTIL
13
12
11
10
9
8
7
6
5
4
2008
2009
2010
2011
2012

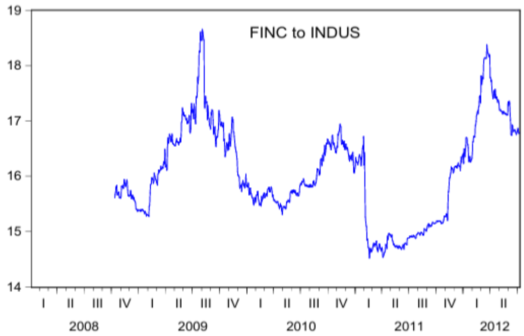

ENRGY to CNSM
13
12
11
10
9
8
2008
2009
2010
2011
2012
ENRGY to COMM
18
16
14
12
10
8
6
2008
2009
2010
2011
2012
ENRGY to FINC
17
16
15
14
13
12
11
10
9
8
2008
2009
2010
2011
2012
ENRGY to HLTH
14
13
12
11
10
9
8
7
6
5
2008
2009
2010
2011
2012
ENRGY to INDUS
17.0
16.5
16.0
15.5
15.0
14.5
14.0
13.5
13.0
2008
2009
2010
2011
2012
ENRGY to MAT
12
10
8
6
4
2
0
2008
2009
2010
2011
2012
ENRGY to TECH
.9
.8
.7
.6
.5
.4
.3
.2
.1
.0
2008
2009
2010
2011
2012
ENRGY to UTIL
16
14
12
10
8
6
4
2008
2009
2010
2011
2012

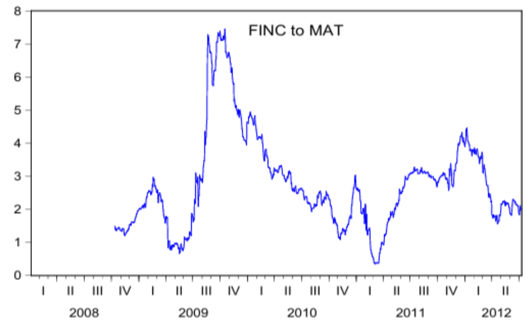

FINC to COMM
14
13
12
11
10
9
8
7
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

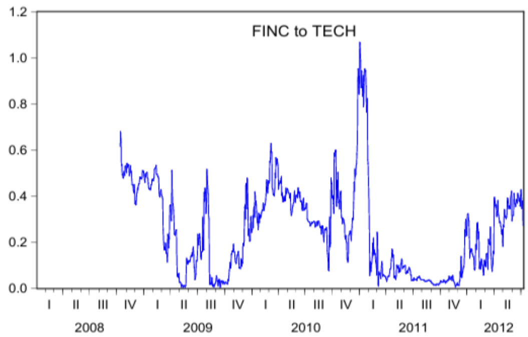

FINC to CNSM
17
16
15
14
13
12
11
10
9
8
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

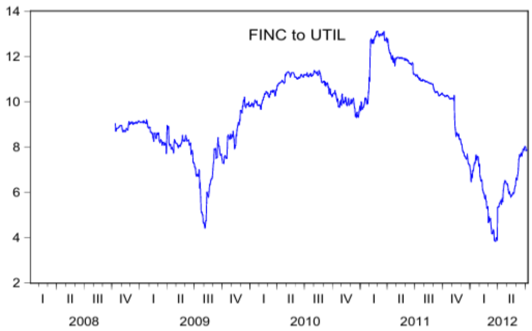

FINC to ENRGY
16
15
14
13
12
11
10
9
8
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

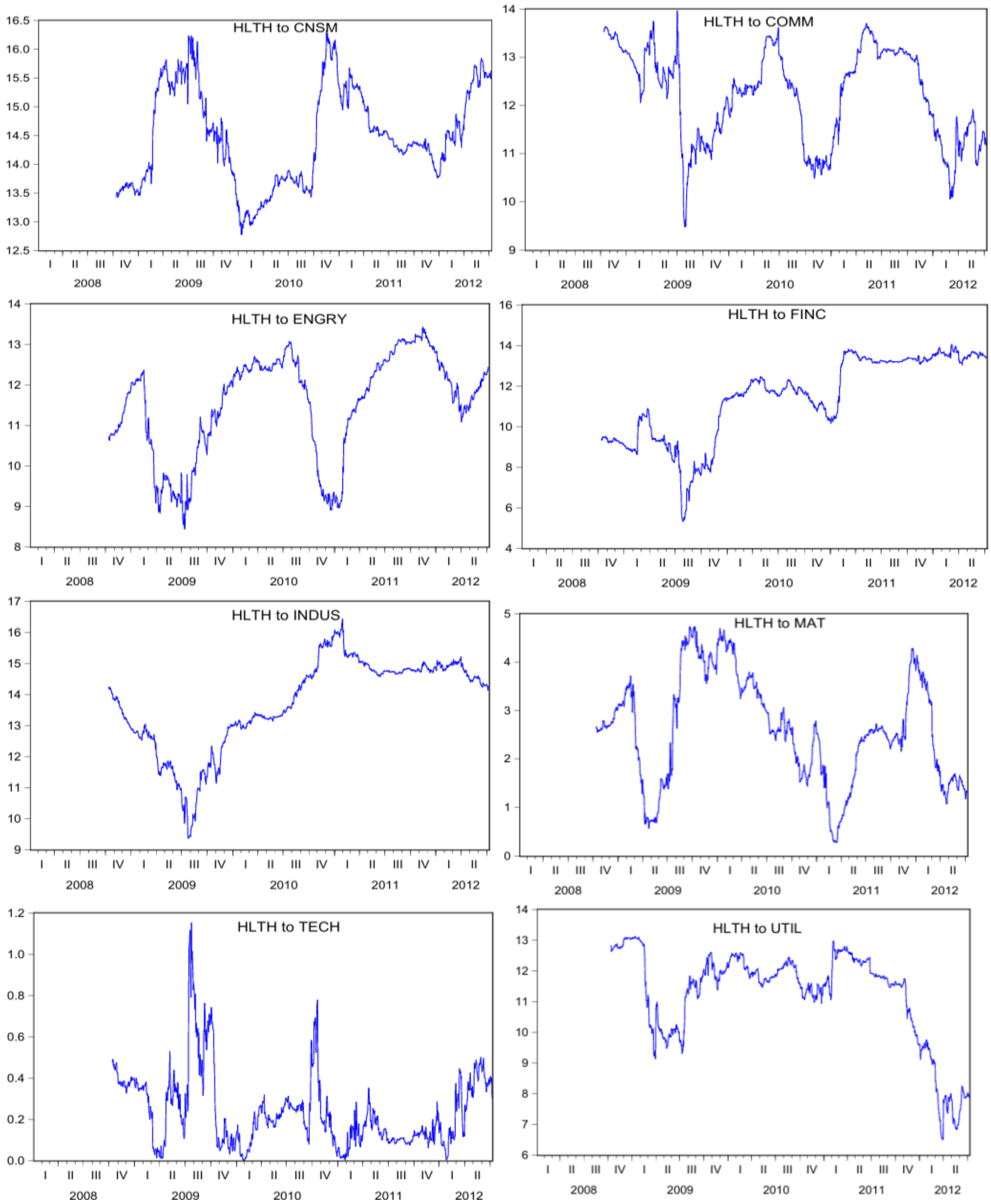

FINC to HLTH
16
14
12
10
8
6
4
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

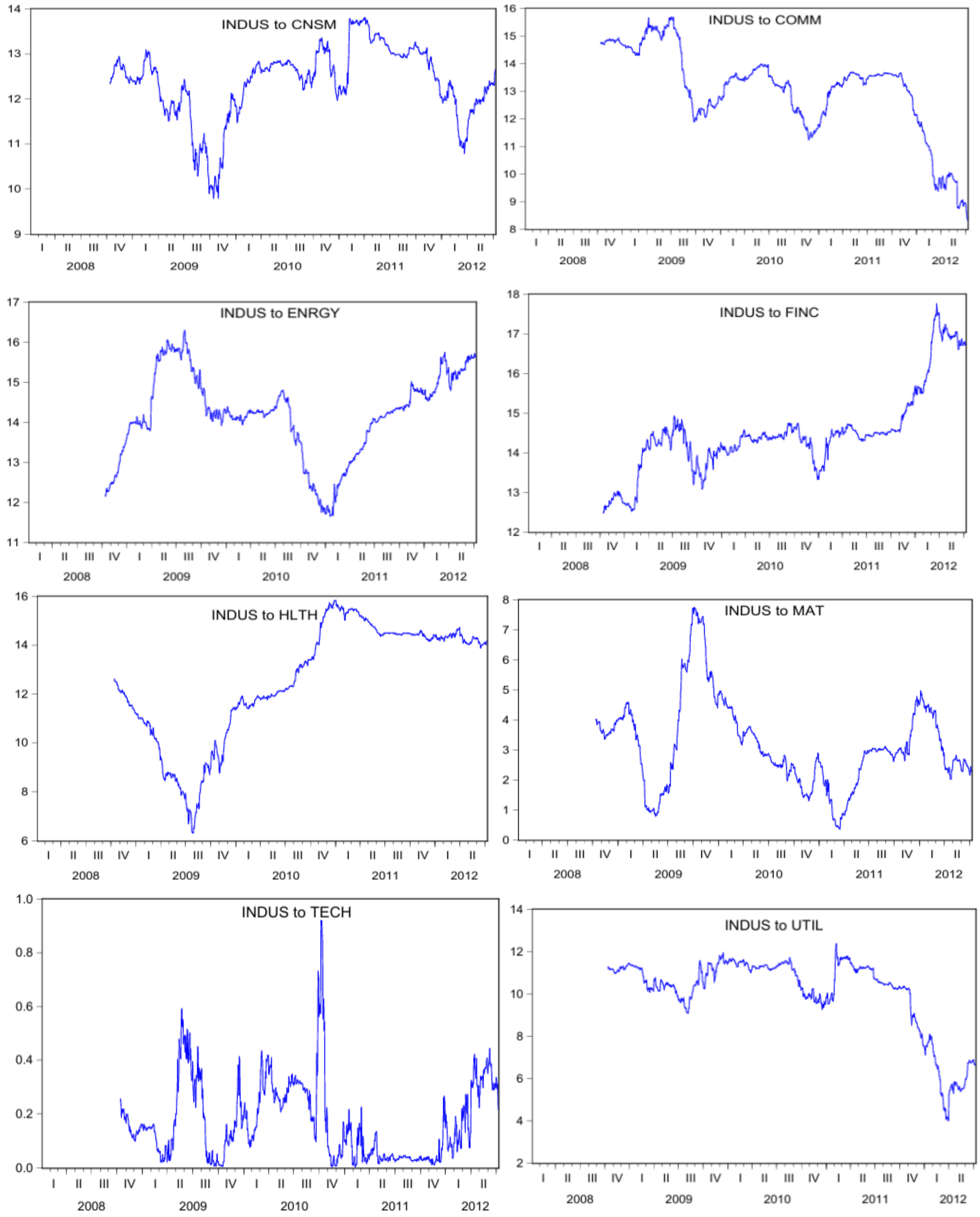

FINC to INDUS
19
18
17
16
15
14
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

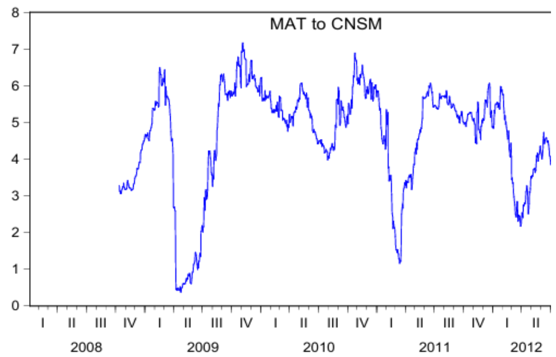

FINC to MAT
8
7
6
5
4
3
2
1
0
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

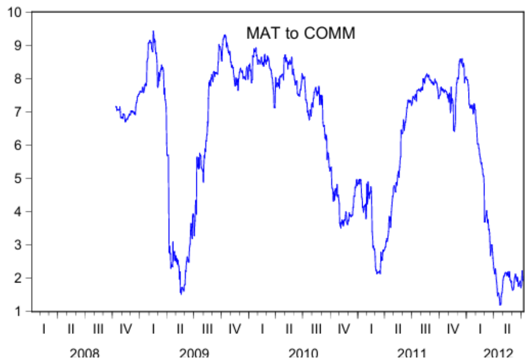

FINC to TECH
1.2
1.0
0.8
0.6
0.4
0.2
0.0
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

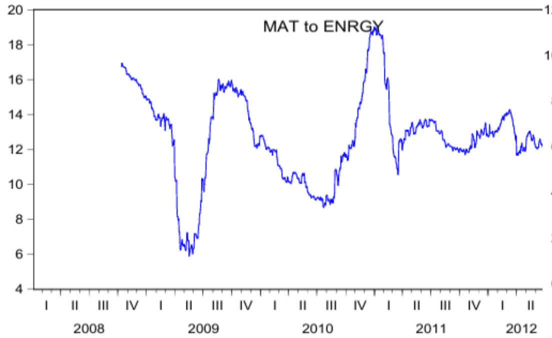

FINC to UTIL
14
12
10
8
6
4
2
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

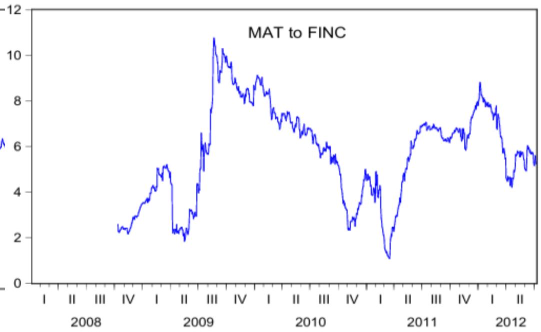

HLTH to CNSM
HLTH to COMM
HLTH to ENGRY
HLTH to FINC
HLTH to INDUS
HLTH to MAT
HLTH to TECH
HLTH to UTIL
I II III IV
2008
2009
2010
2011
2012

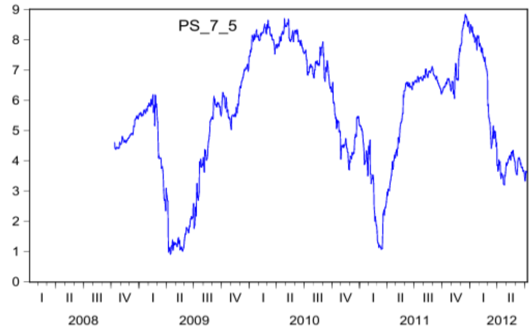

INDUS to CNSM
INDUS to COMM
INDUS to ENRGY
INDUS to FINC
INDUS to HLTH
INDUS to MAT
INDUS to TECH
INDUS to UTIL
I II III IV I II III IV I II III IV I II III IV I II
2008 2009 2010 2011 2012

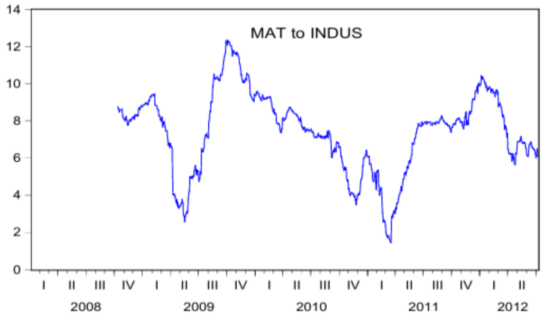

MAT to CNSM
2008
2009
2010
2011
2012

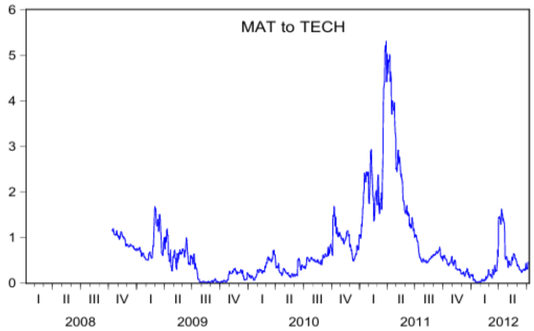

MAT to COMM
2008
2009
2010
2011
2012

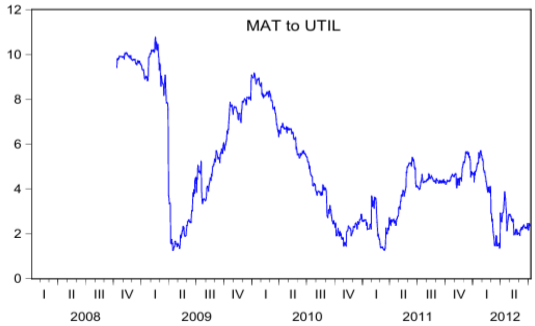

MAT to ENRGY
2008
2009
2010
2011
2012

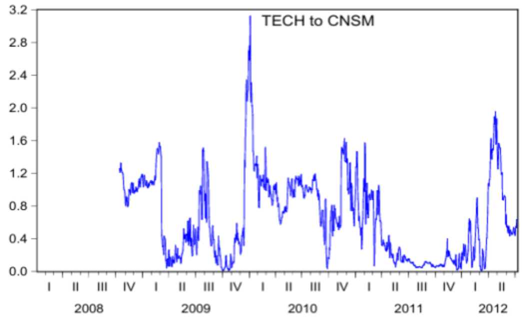
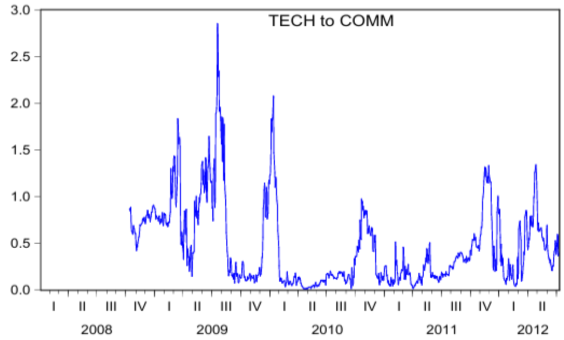
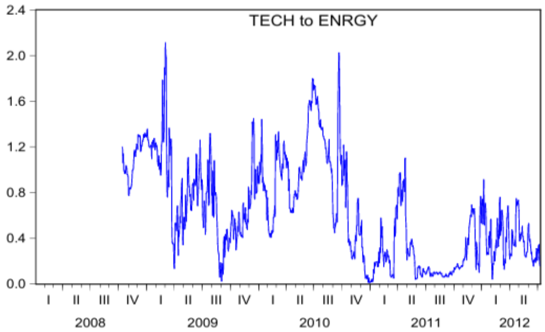
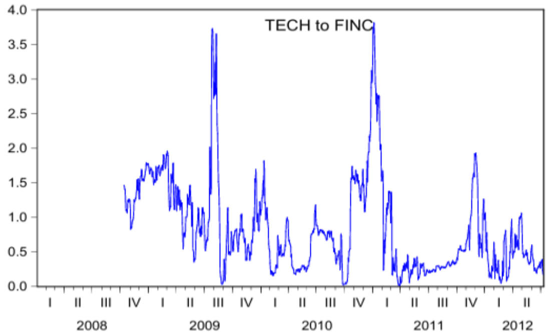
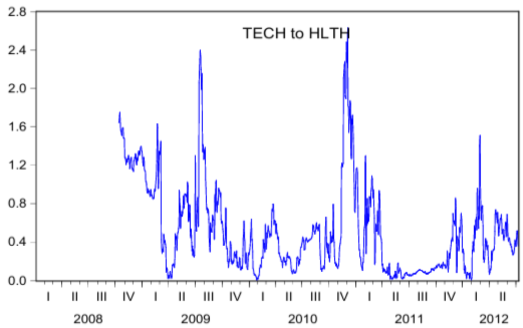
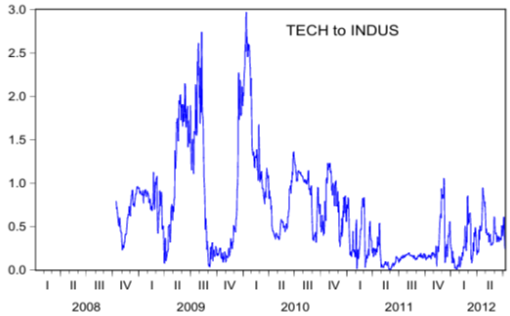
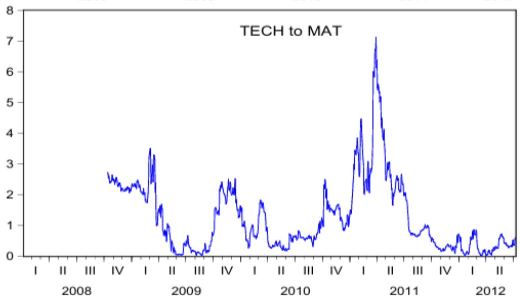
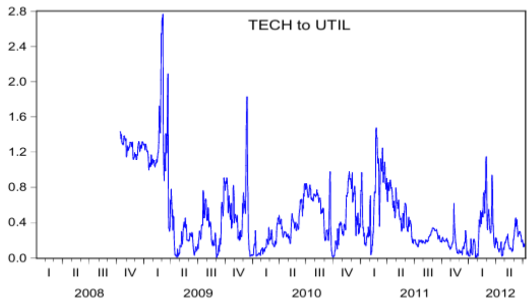

MAT to FINC
2008
2009
2010
2011
2012

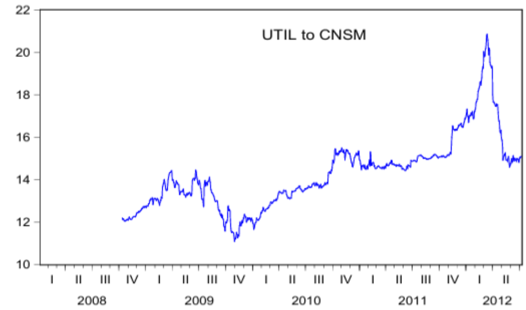

PS_7_5
2008
2009
2010
2011
2012

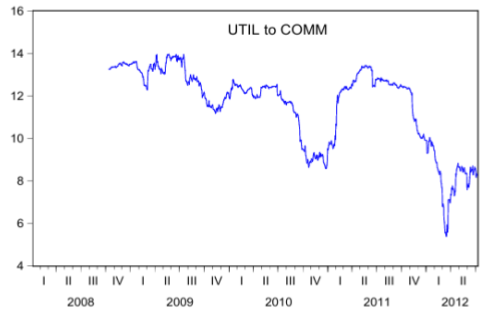

MAT to INDUS
2008
2009
2010
2011
2012

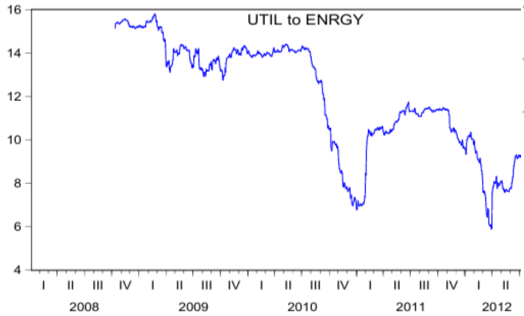

MAT to TECH
2008
2009
2010
2011
2012

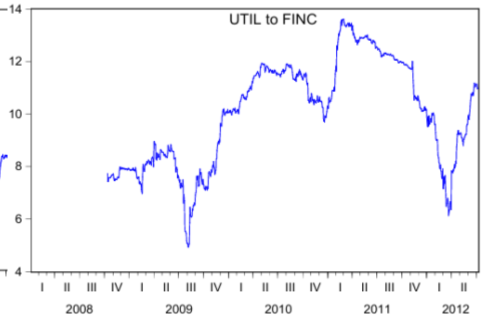

MAT to UTIL
2008
2009
2010
2011
2012

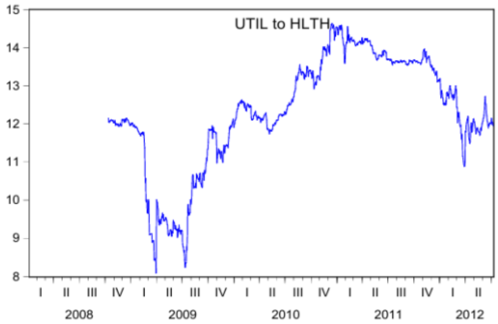

TECH to CNSM
2008
2009
2010
2011
2012

TECH to COMM
2008
2009
2010
2011
2012

TECH to ENRGY
2008
2009
2010
2011
2012

TECH to FINC
2008
2009
2010
2011
2012

TECH to HLTH
2008
2009
2010
2011
2012

TECH to INDUS
2008
2009
2010
2011
2012

TECH to MAT
2008
2009
2010
2011
2012

TECH to UTIL
2008
2009
2010
2011
2012

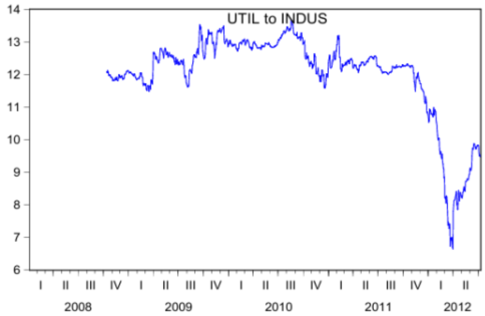

UTIL to CNSM

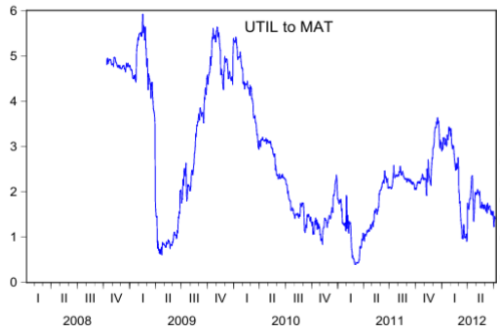

UTIL to COMM

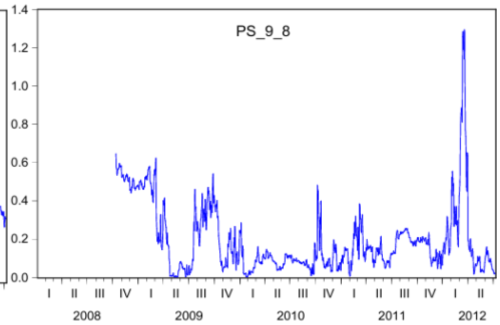

UTIL to ENRGY


UTIL to FINC

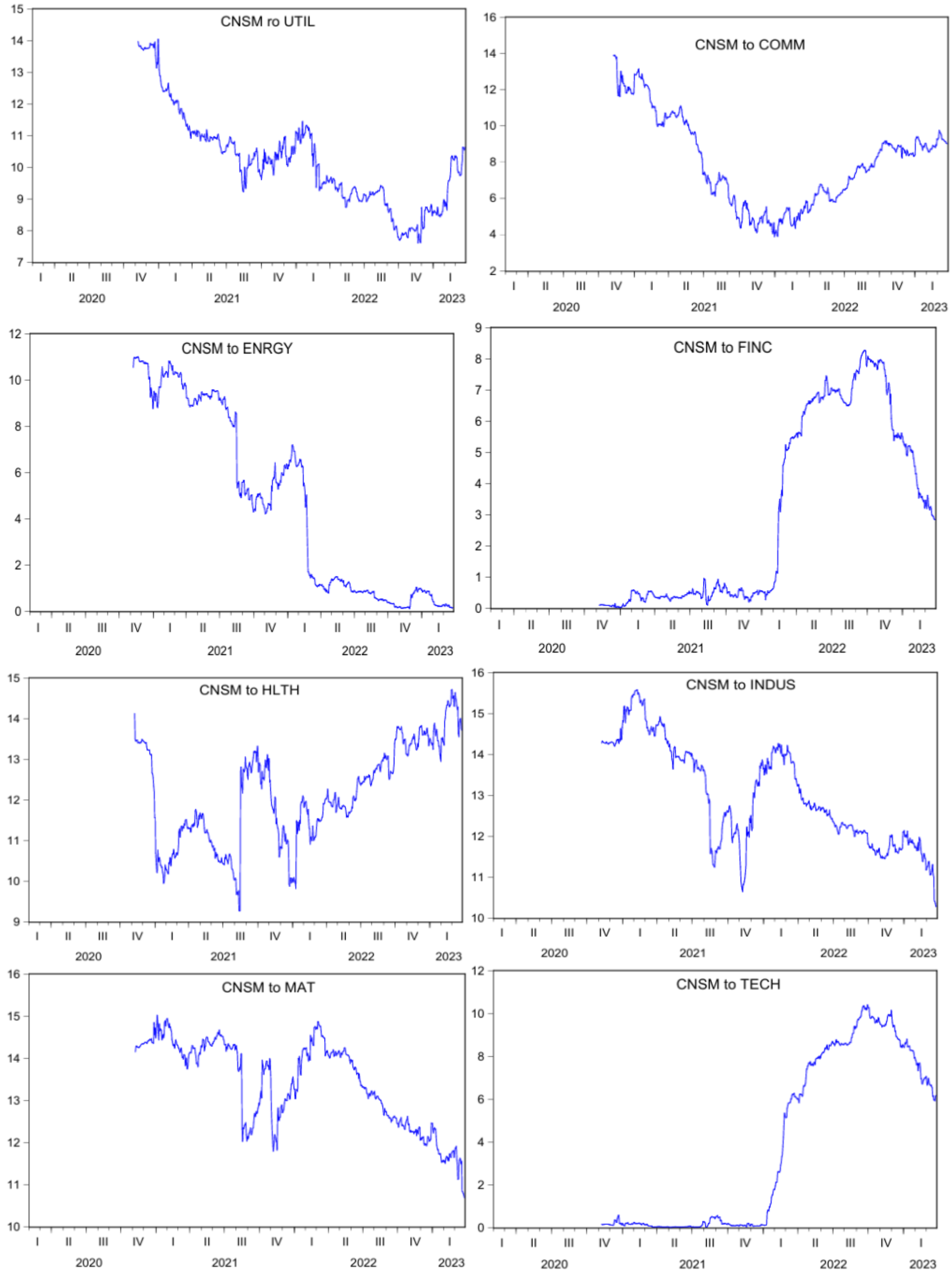

UTIL to HLTH

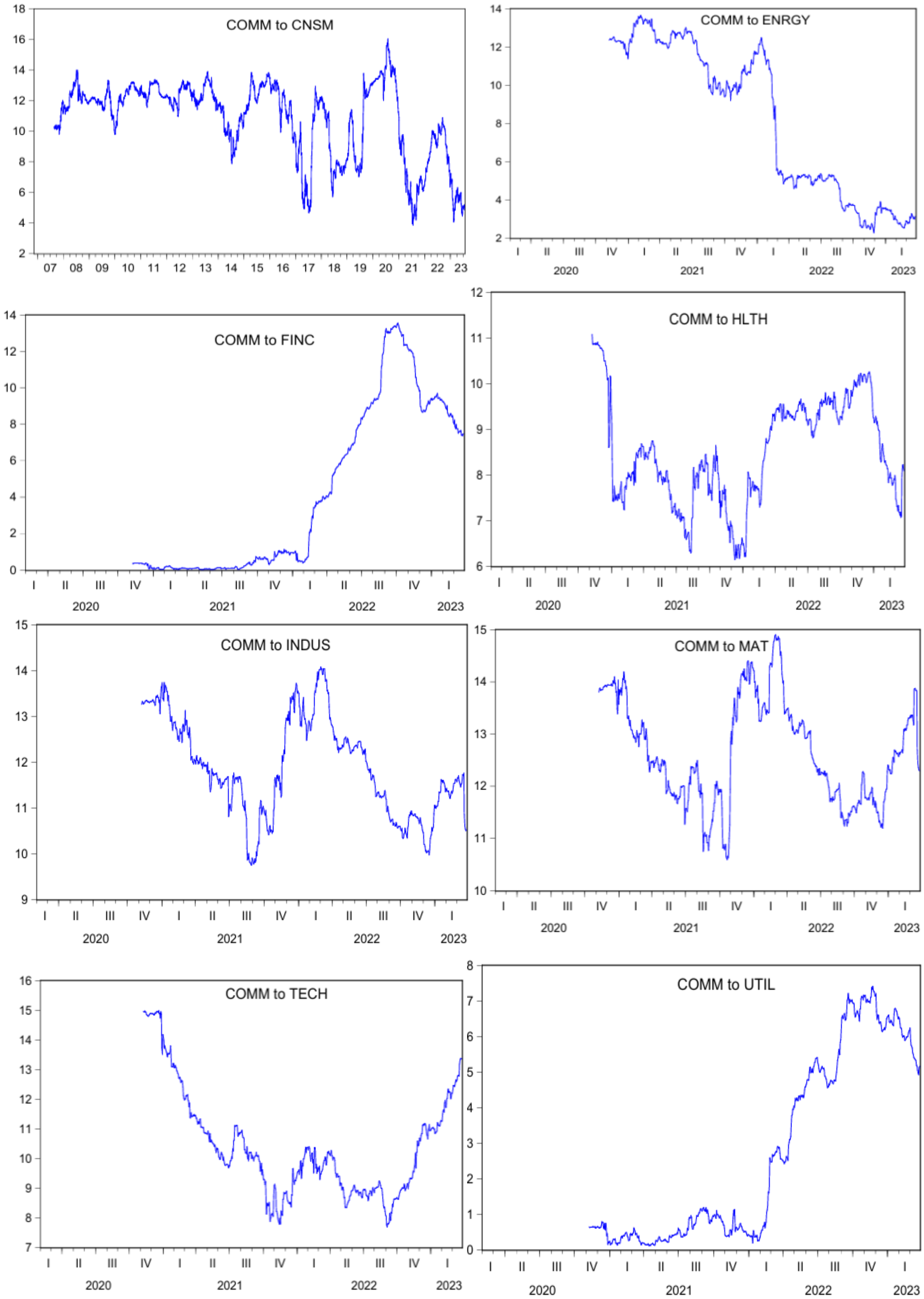

UTIL to INDUS

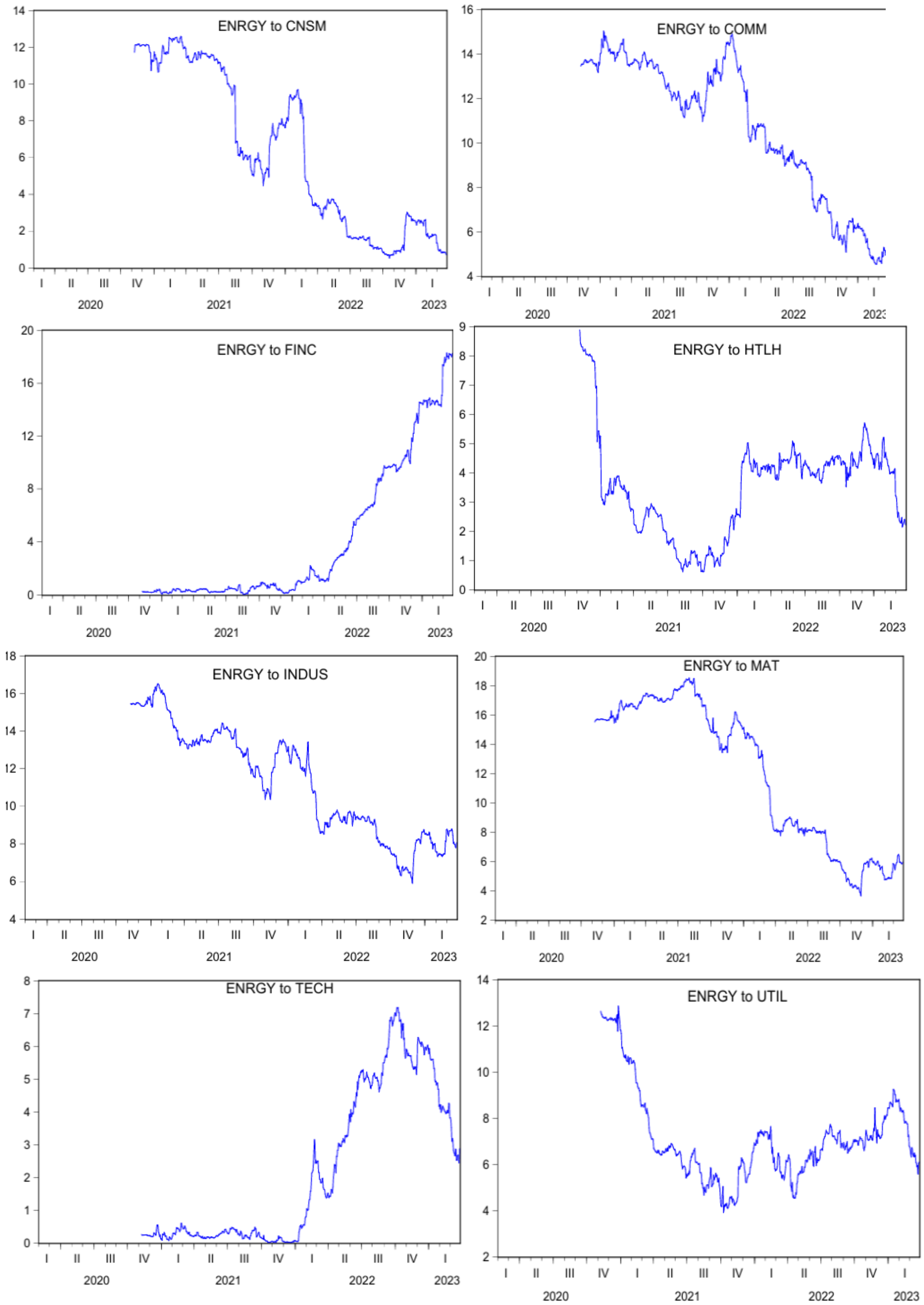

UTIL to MAT

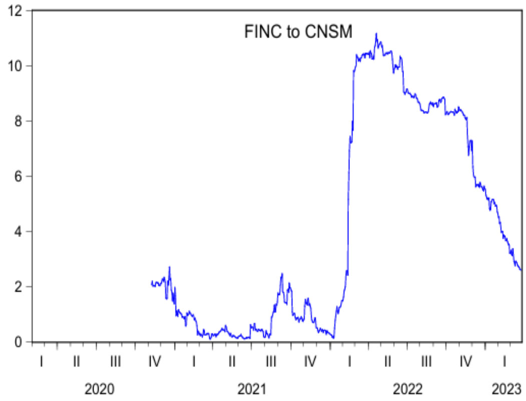

PS_9_8

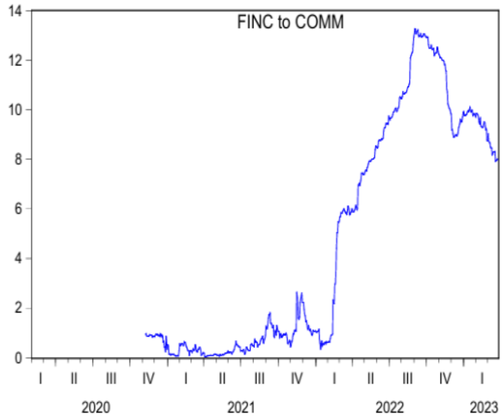
Sample Period 3 Dynamic Connectedness EU Sectors

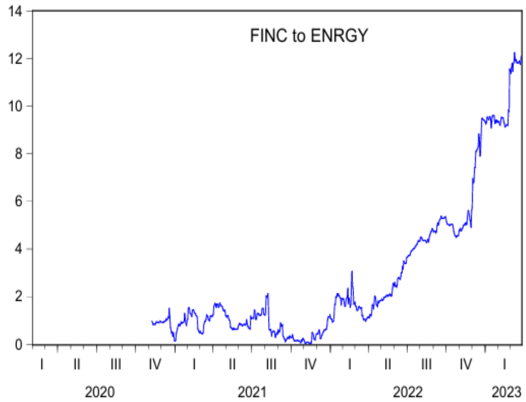


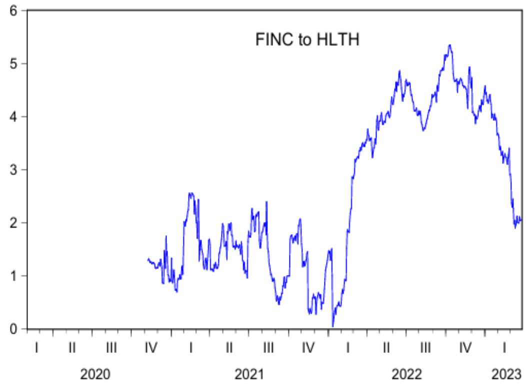

COMM to CNSM
COMM to ENRGY
COMM to FINC
COMM to HLTH
COMM to INDUS
COMM to MAT
COMM to TECH
COMM to UTIL

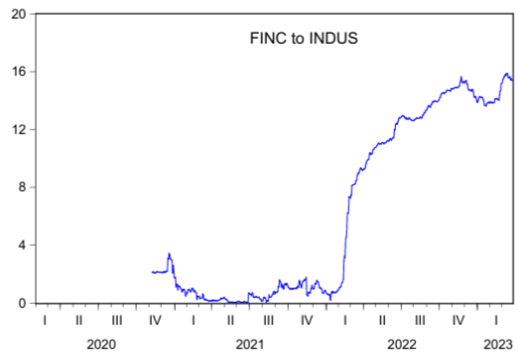

ENRGY to CNSM
ENRGY to COMM
ENRGY to FINC
ENRGY to HTLH
ENRGY to INDUS
ENRGY to MAT
ENRGY to TECH
ENRGY to UTIL

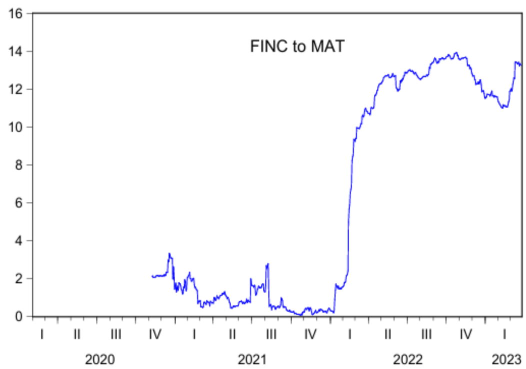

FINC to CNSM


FINC to COMM

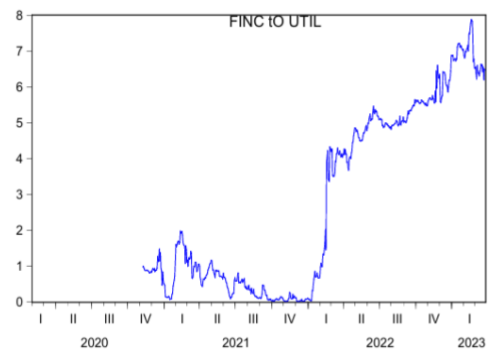

FINC to ENRGY

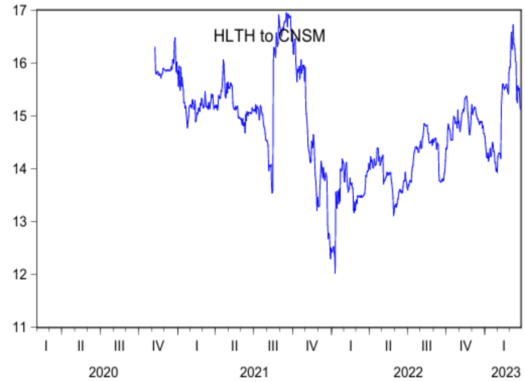

FINC to HLTH


FINC to INDUS


FINC to MAT


FINC tO TECH


FINC tO UTIL


HLTH to CNSM
17
16
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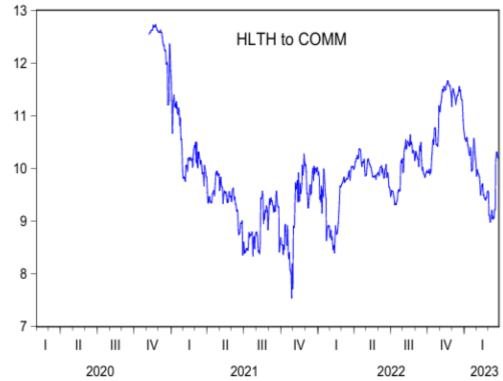
12
11
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to COMM
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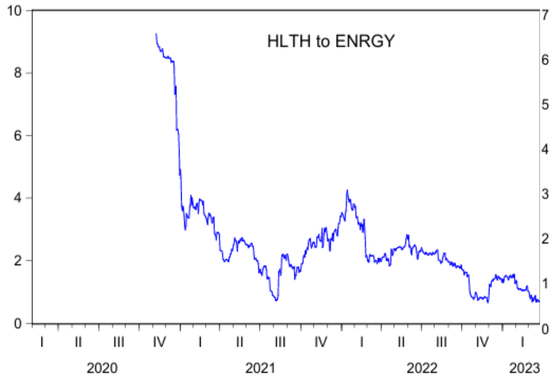
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to ENRGY
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8
6
4
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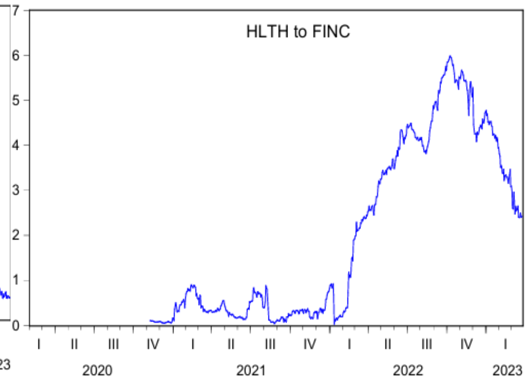
0
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to FINC
7
6
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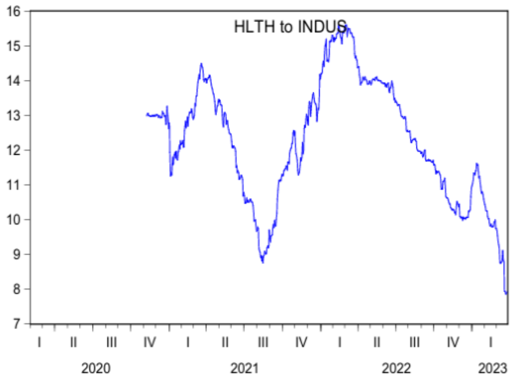
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to INDUS
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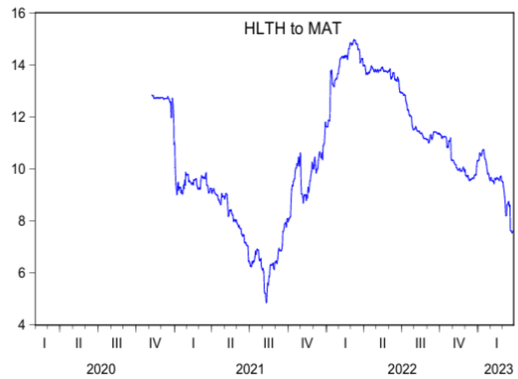
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to MAT
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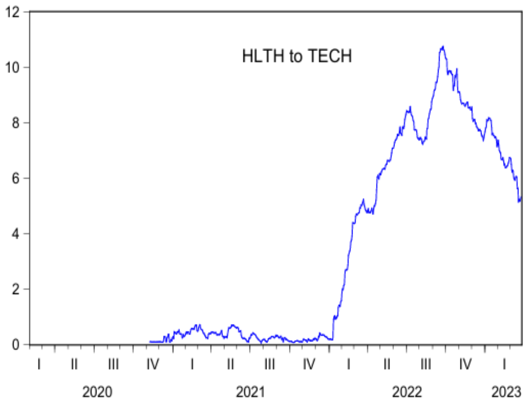
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to TECH
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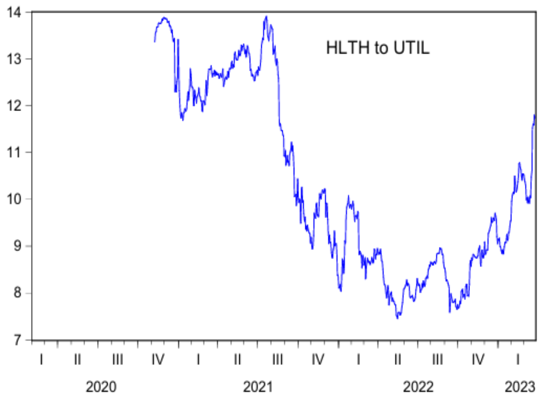
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


HLTH to UTIL
14
13
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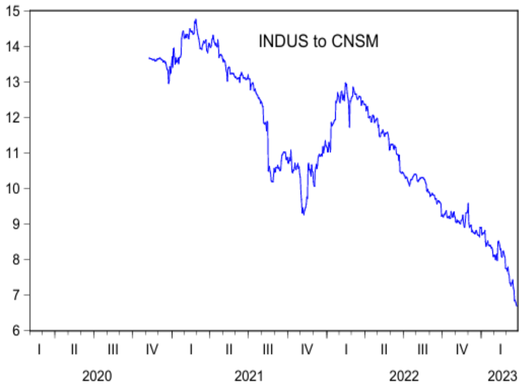
7
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to CNSM
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13
12
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8
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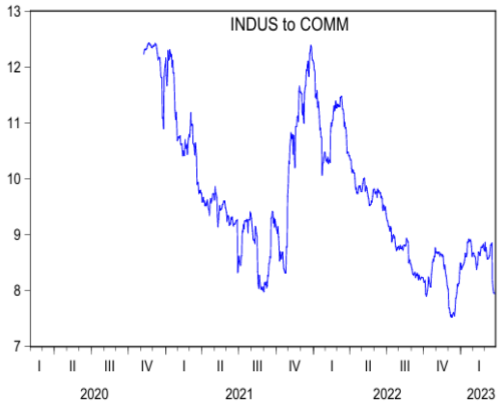
6
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to COMM
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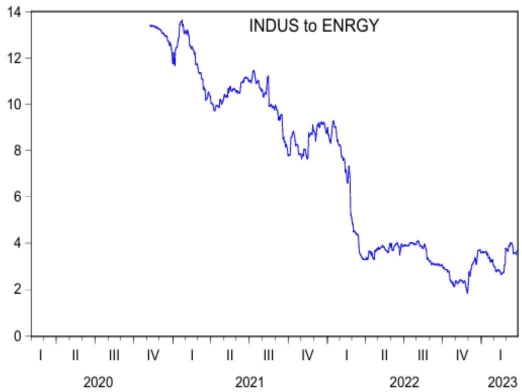
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to ENRGY
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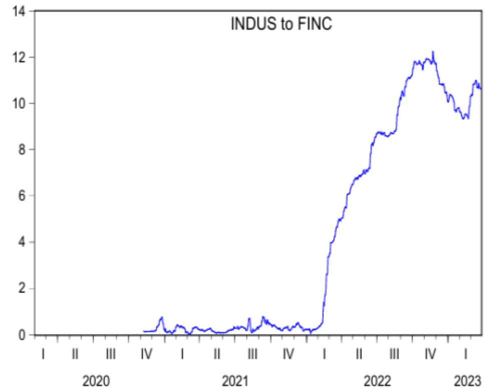
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to FINC
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12
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I II III IV I II III IV I II III IV I
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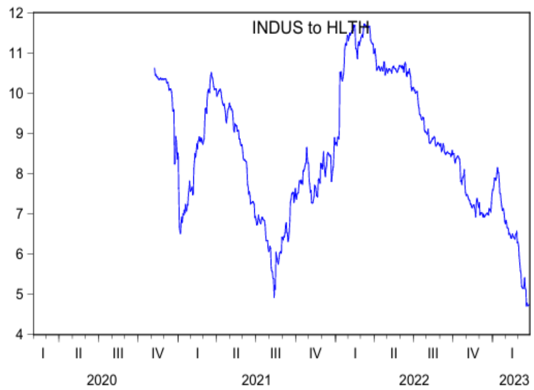
INDUS to HLTH
12
11
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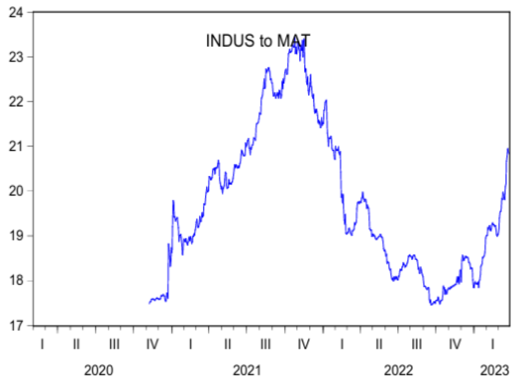
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to MAT
24
23
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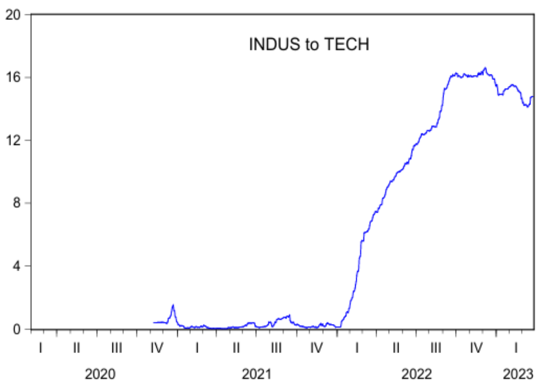
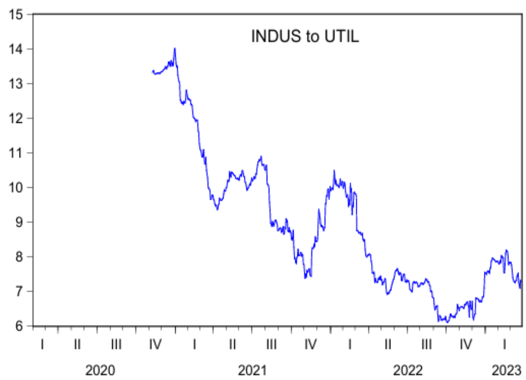
21
20
19
18
17
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to TECH
20
16
12
8
4
0
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


INDUS to UTIL
15
14
13
12
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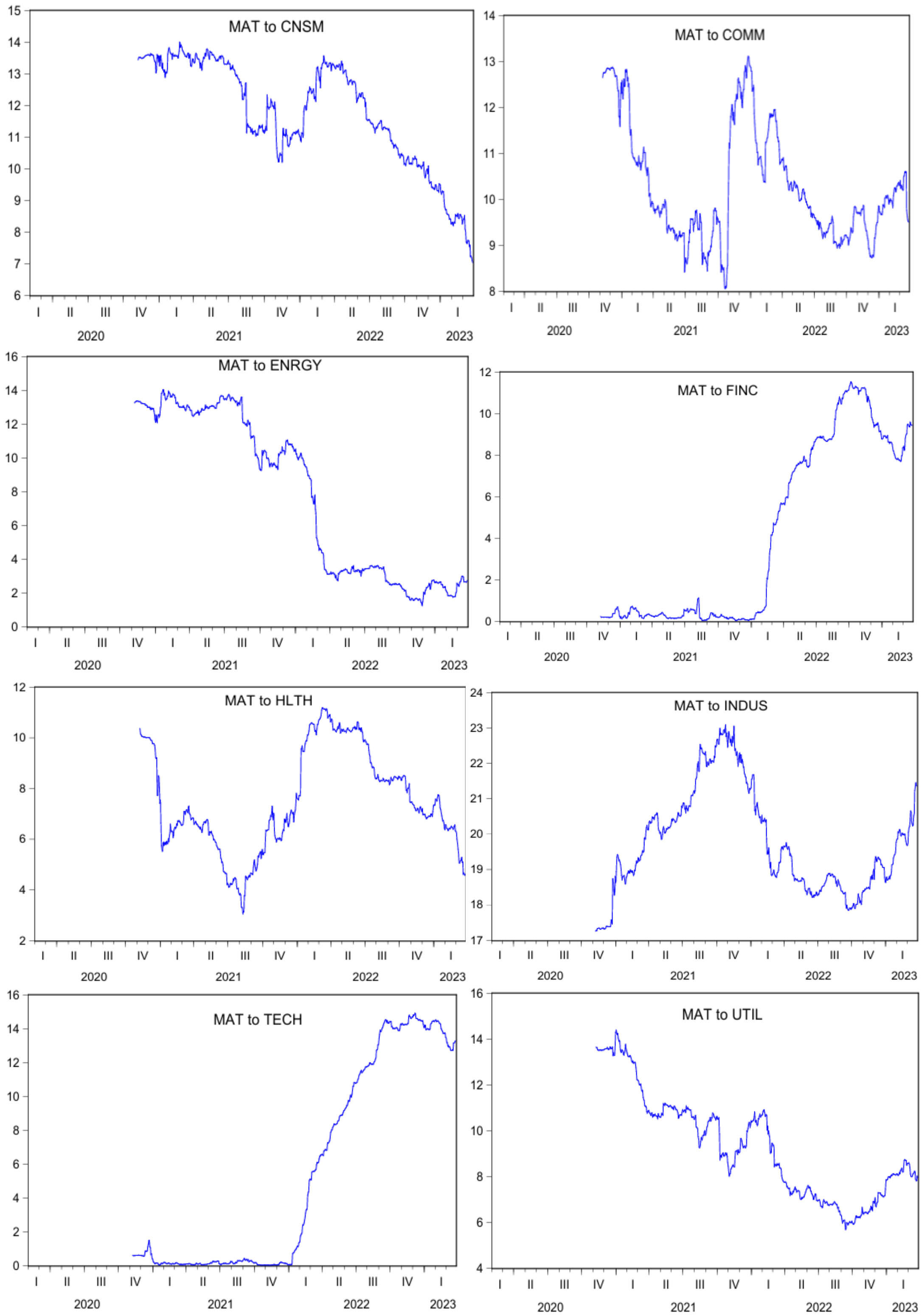
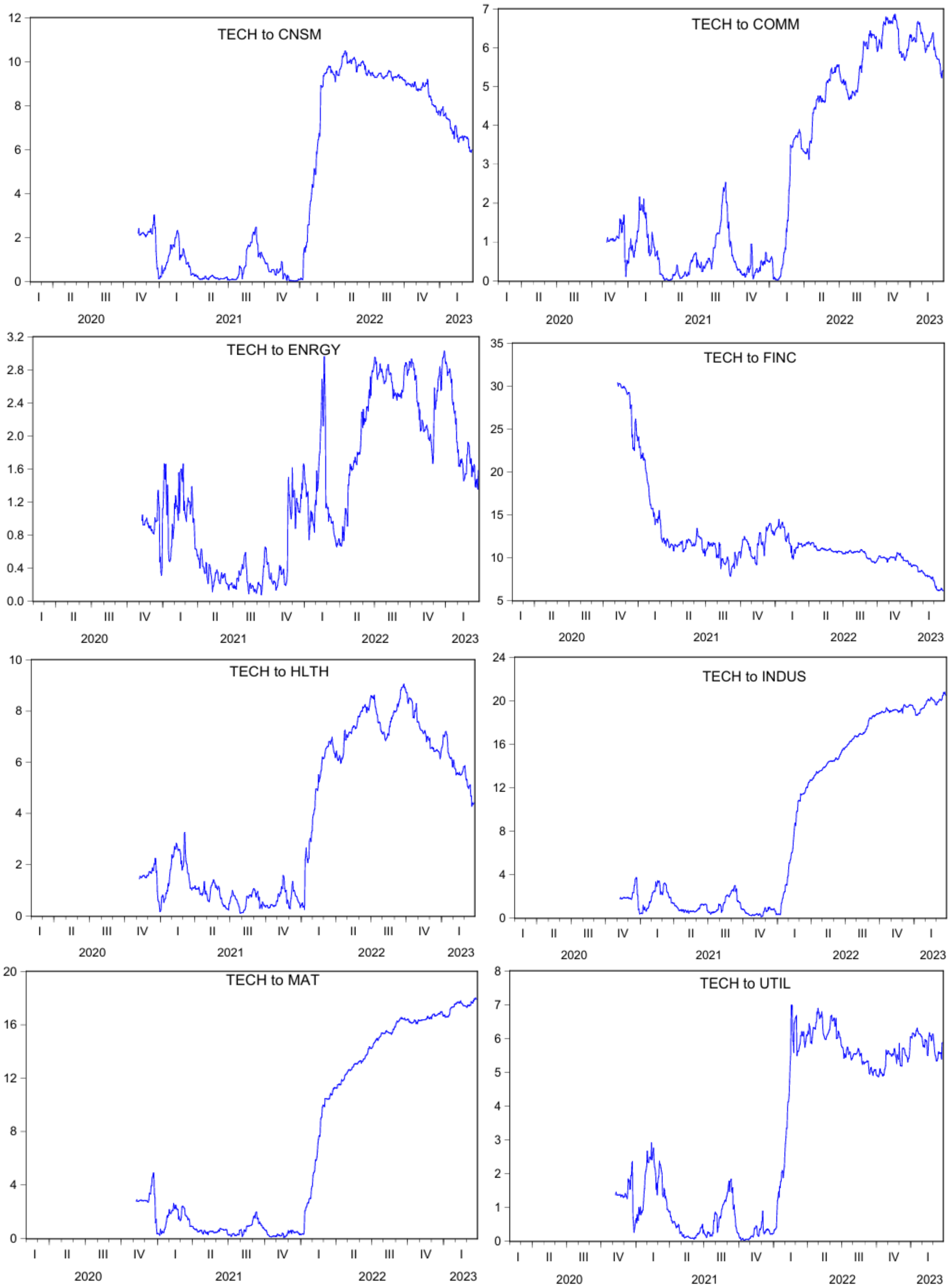
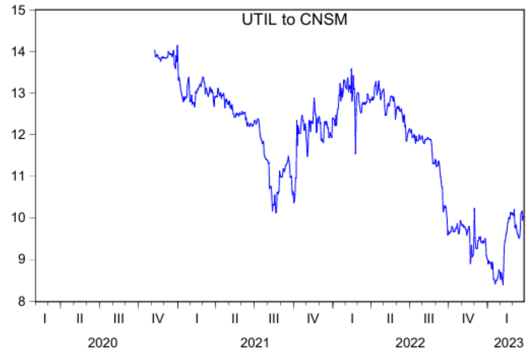
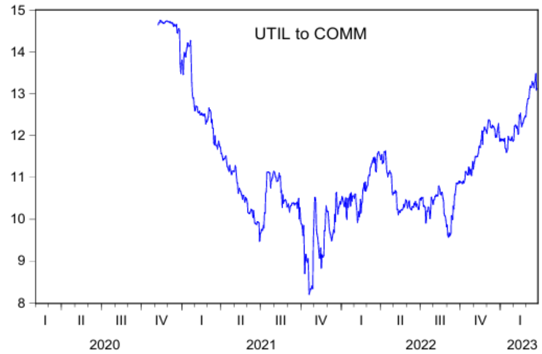
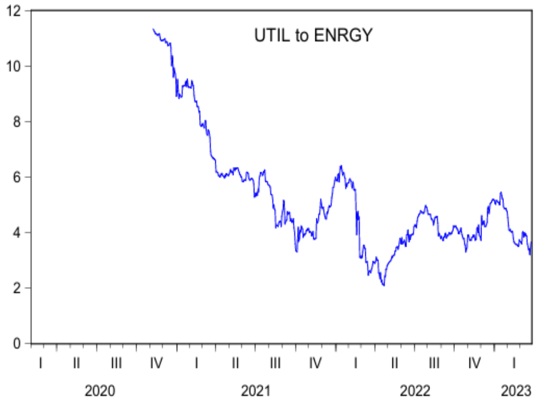
10
9
8
7
6
I II III IV I II III IV I II III IV I
2020 2021 2022 2023

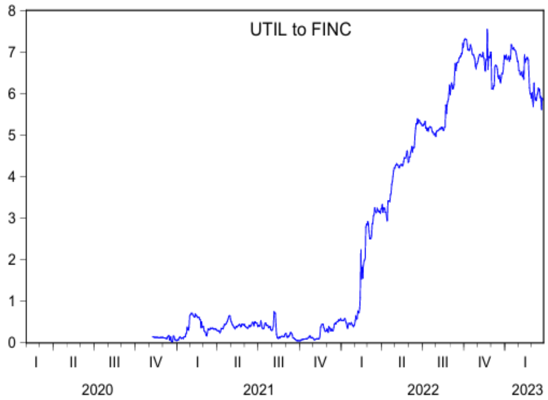

MAT to CNSM
MAT to COMM
MAT to ENRGY
MAT to FINC
MAT to HLTH
MAT to INDUS
MAT to TECH
MAT to UTIL

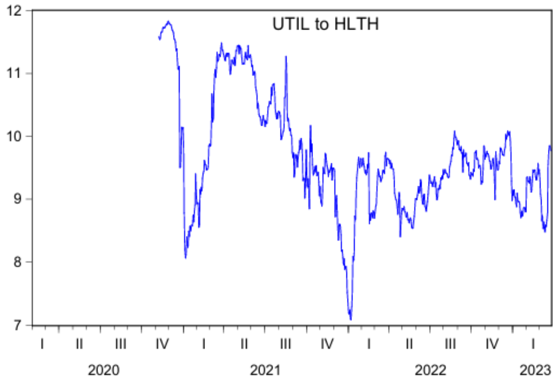

TECH to CNSM
TECH to COMM
TECH to ENRGY
TECH to FINC
TECH to HLTH
TECH to INDUS
TECH to MAT
TECH to UTIL
2020
2021
2022
2023

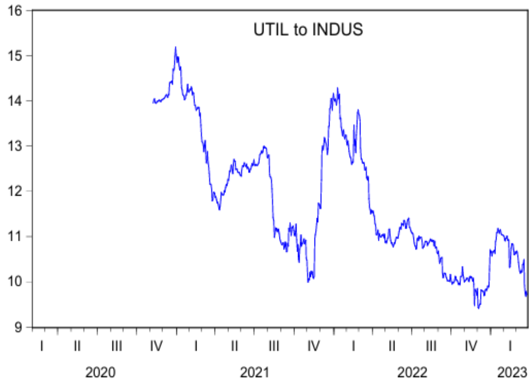

UTIL to CNSM
2020
2021
2022
2023

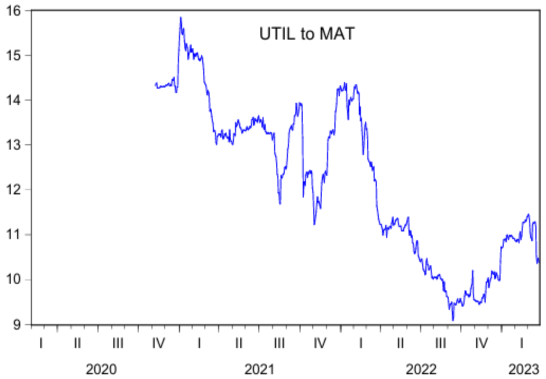

UTIL to COMM
2020
2021
2022
2023

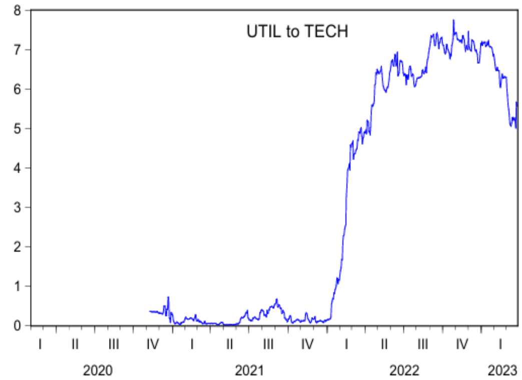

UTIL to ENRGY
2020
2021
2022
2023


UTIL to FINC
2020
2021
2022
2023

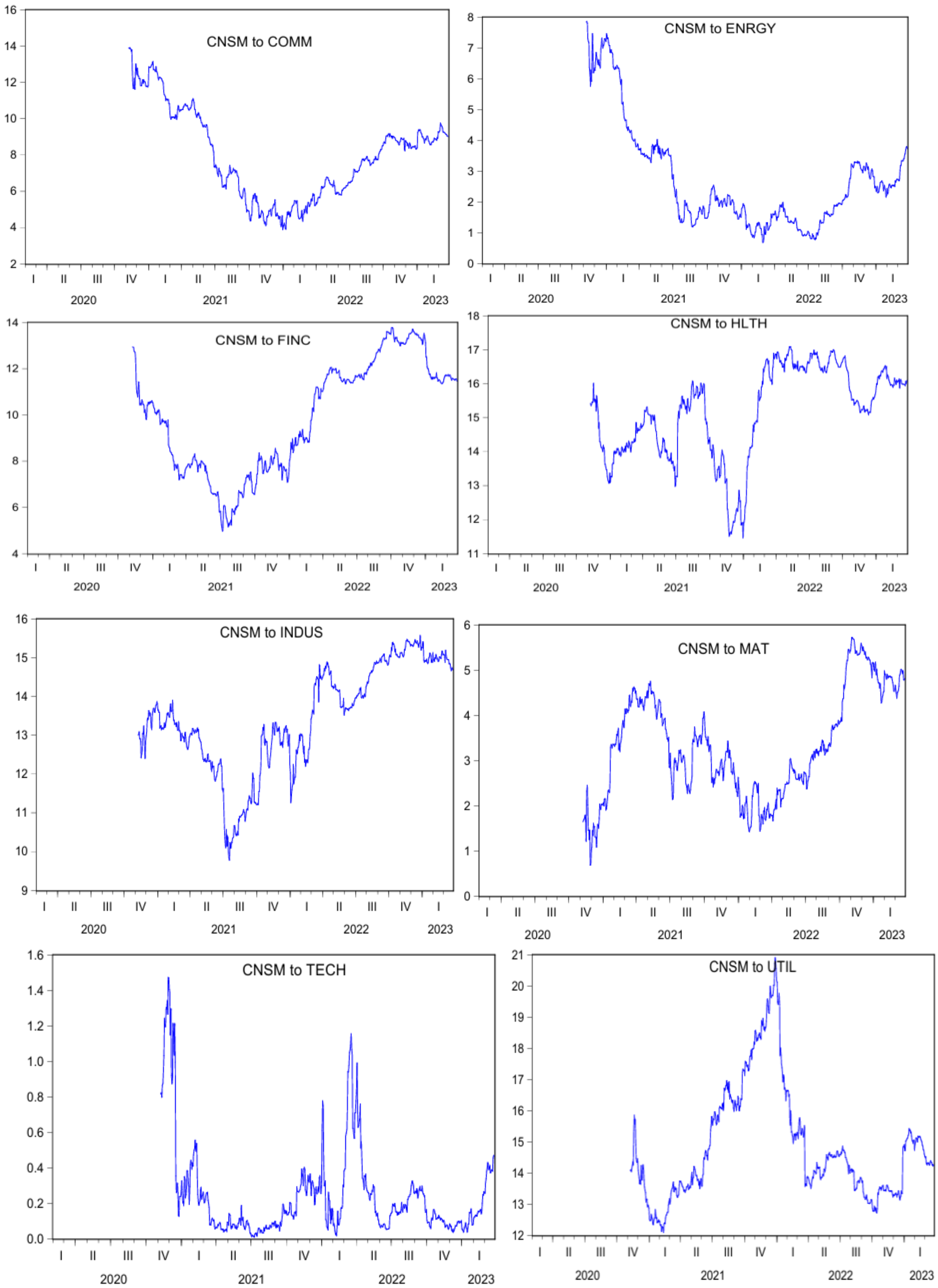

UTIL to HLTH
2020
2021
2022
2023

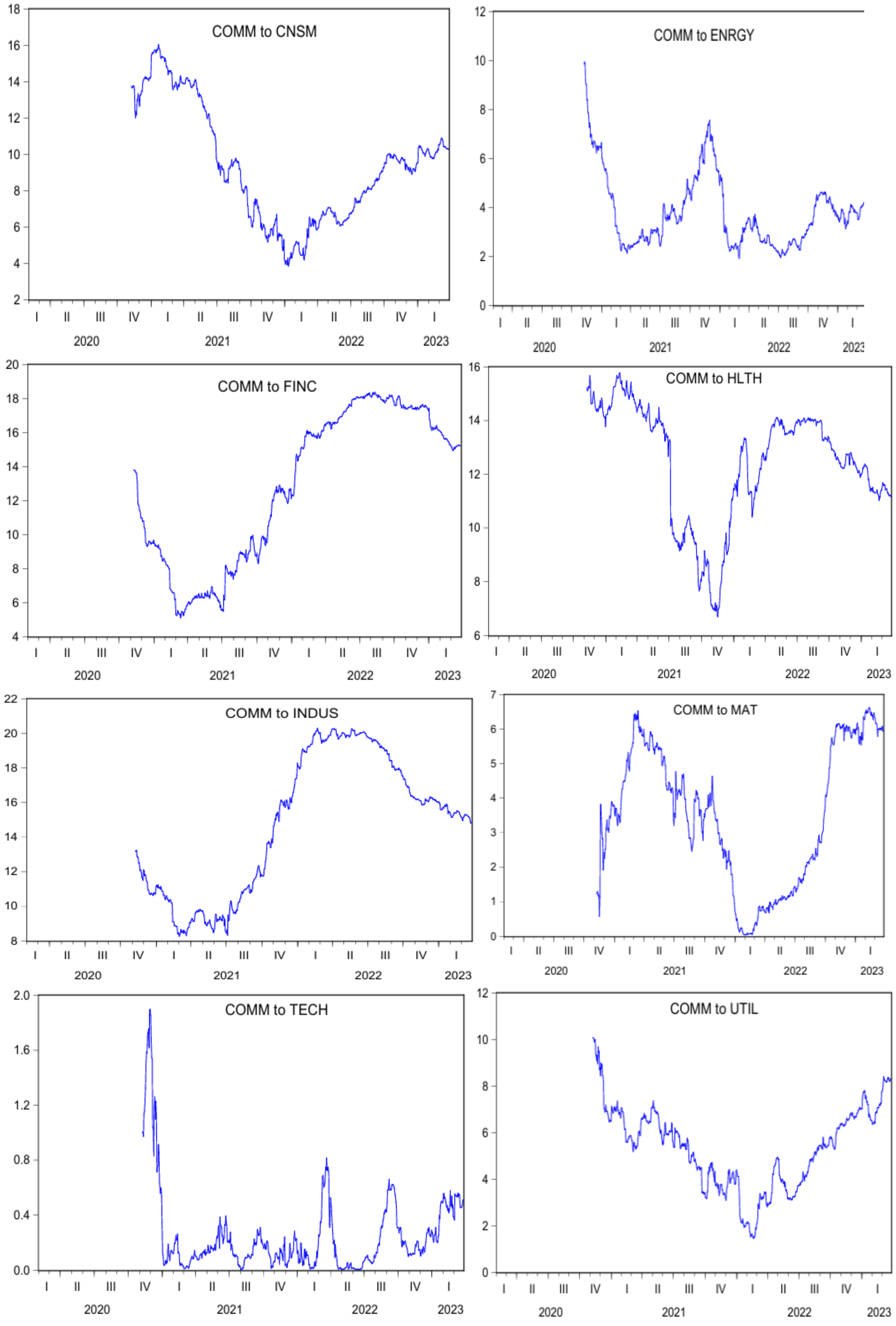

UTIL to INDUS
2020
2021
2022
2023

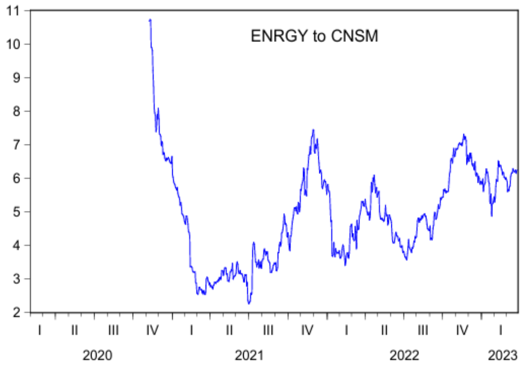

UTIL to MAT
2020
2021
2022
2023

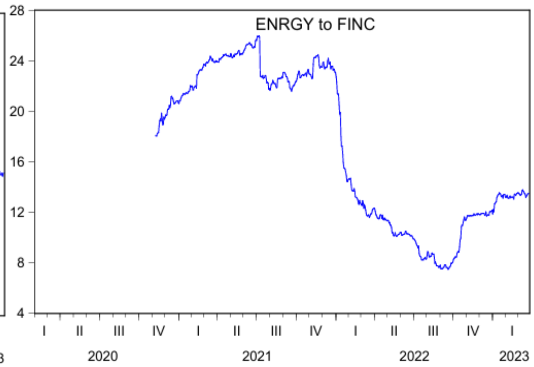

UTIL to TECH
2020
2021
2022
2023

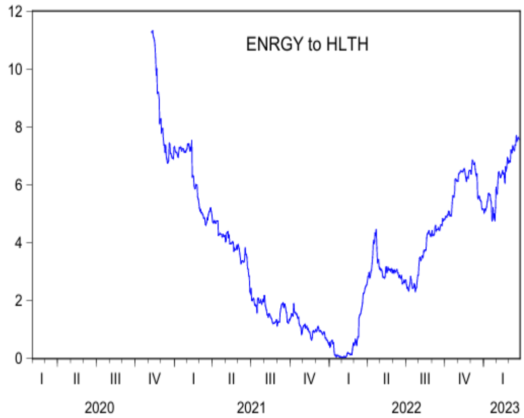
Sample Period 3 Dynamic Connectedness US Sectors




COMM to CNSM
COMM to ENRGY
COMM to FINC
COMM to HLTH
COMM to INDUS
COMM to MAT
COMM to TECH
COMM to UTIL
I II III IV I II III IV I II III IV I
2020 2021 2022 2023


ENRGY to CNSM
11
10
9
8
7
6
5
4
3
2
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


ENRGY to FINC
28
24
20
16
12
8
4
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


ENRGY to HLTH
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8
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4
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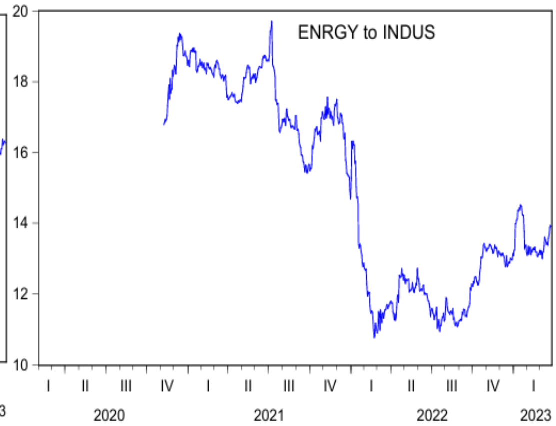
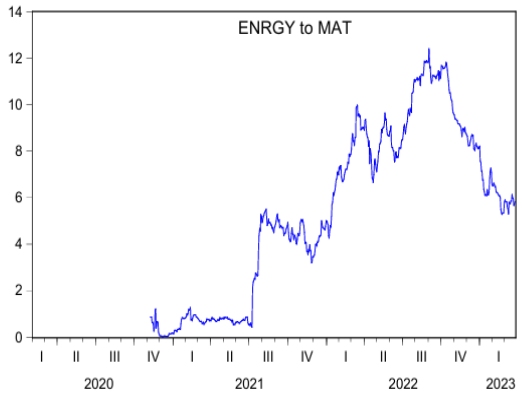
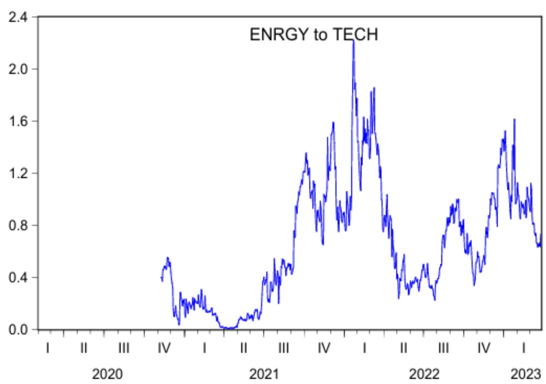
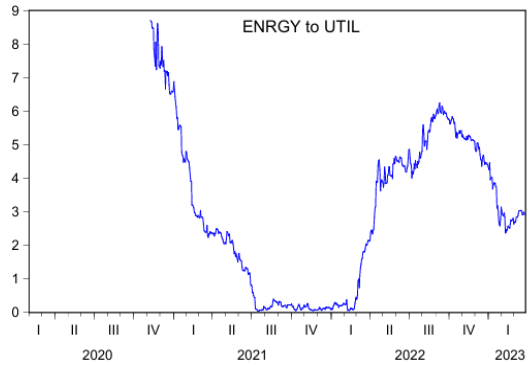
0
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


ENRGY to INDUS
20
18
16
14
12
10
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


ENRGY to MAT
14
12
10
8
6
4
2
0
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


ENRGY to TECH
2.4
2.0
1.6
1.2
0.8
0.4
0.0
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


ENRGY to UTIL
9
8
7
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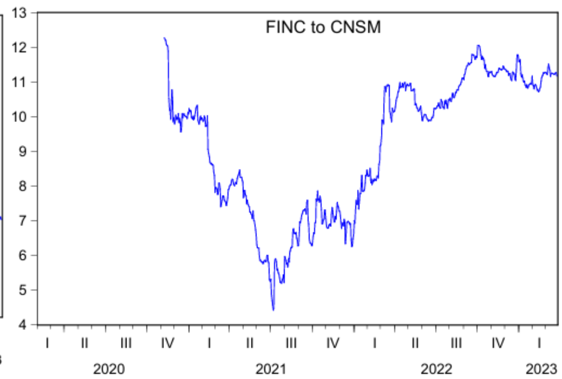
5
4
3
2
1
0
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


FINC to CNSM
13
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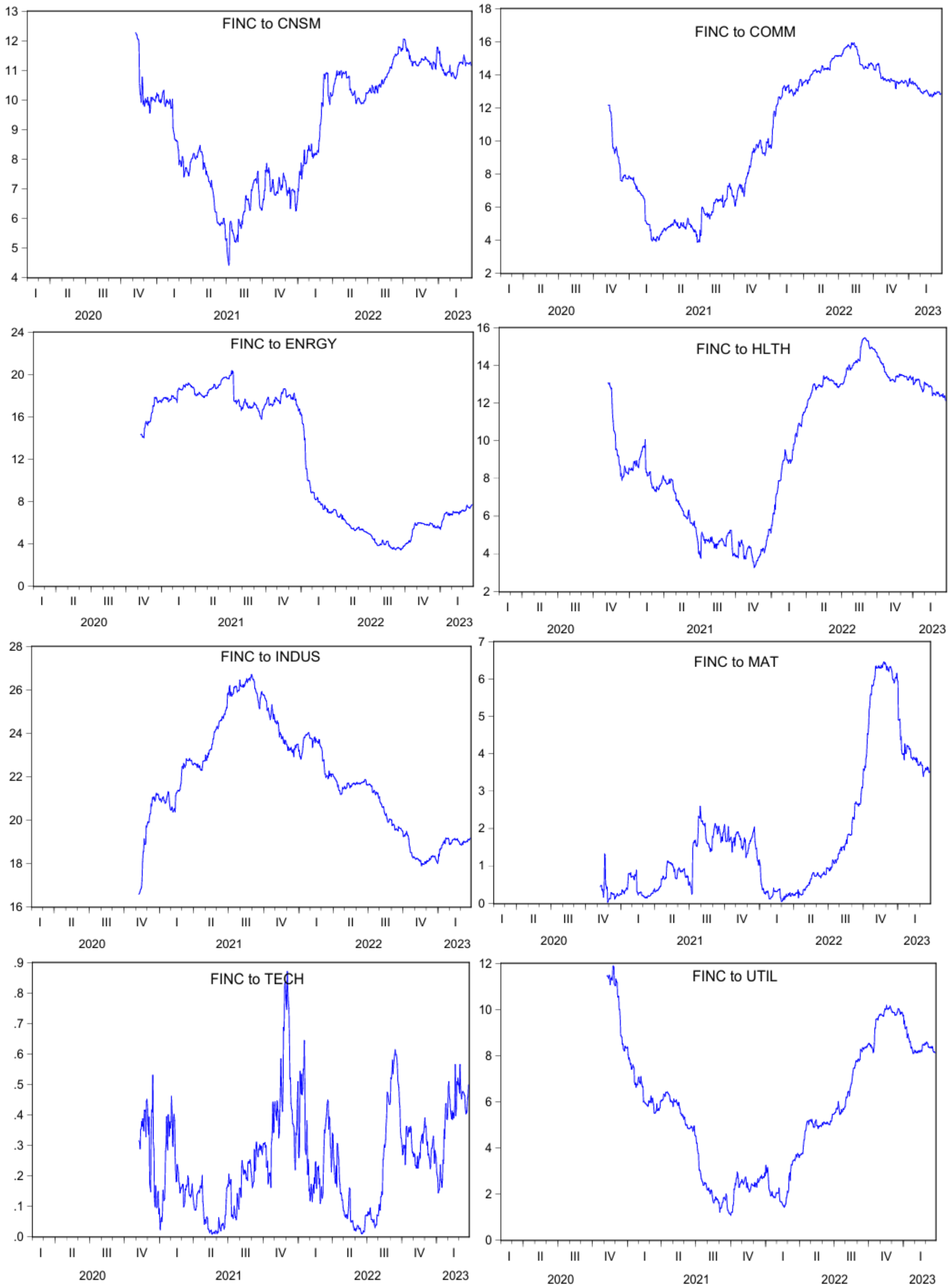
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


FINC to CNSM
FINC to COMM
FINC to ENRGY
FINC to HLTH
FINC to INDUS
FINC to MAT
FINC to TECH
FINC to UTIL
2020
2021
2022
2023


HLTH to CNSM
19
18
17
16
15
14
13
12
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


HLTH to COMM
15
14
13
12
11
10
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8
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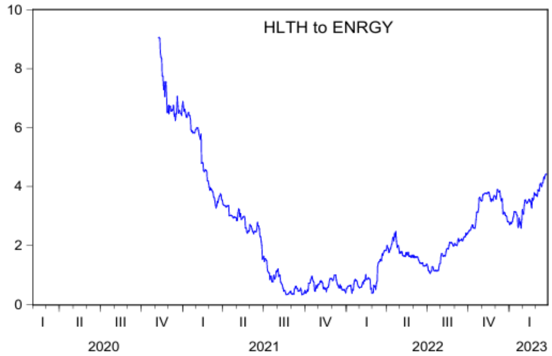
6
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


HLTH to ENRGY
10
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I II III IV I II III IV I II III IV I
2020
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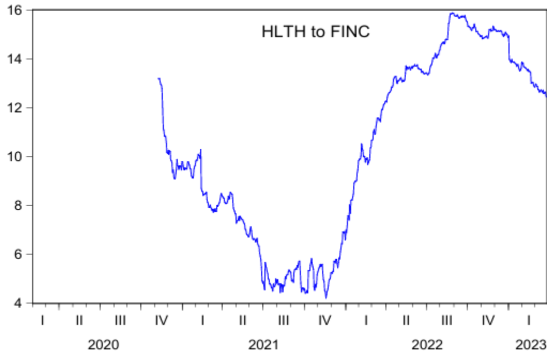
HLTH to FINC
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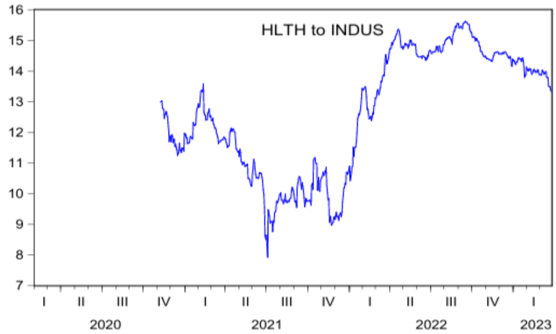
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


HLTH to INDUS
16
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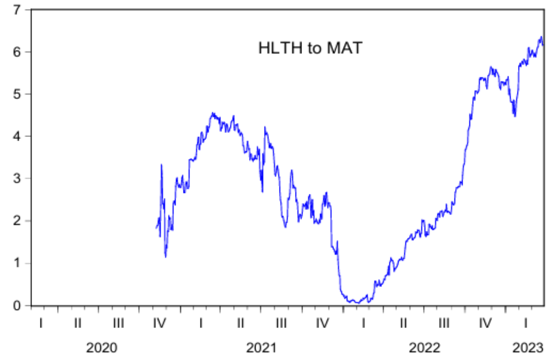
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


HLTH to MAT
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5
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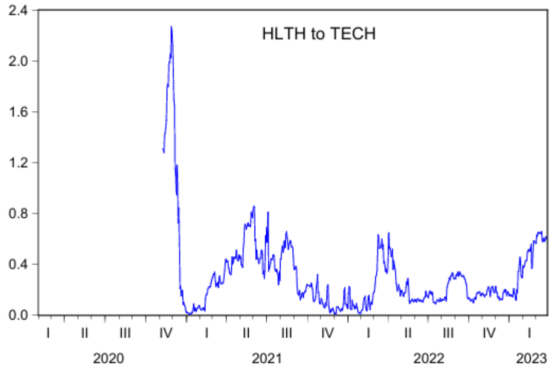
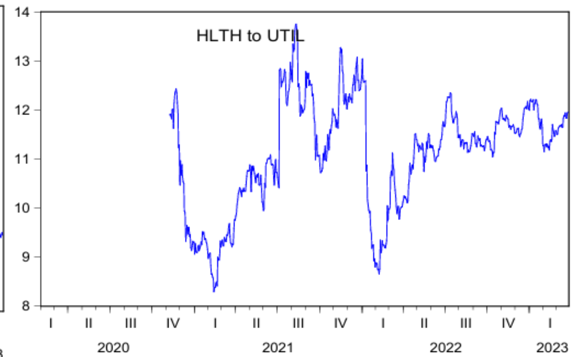
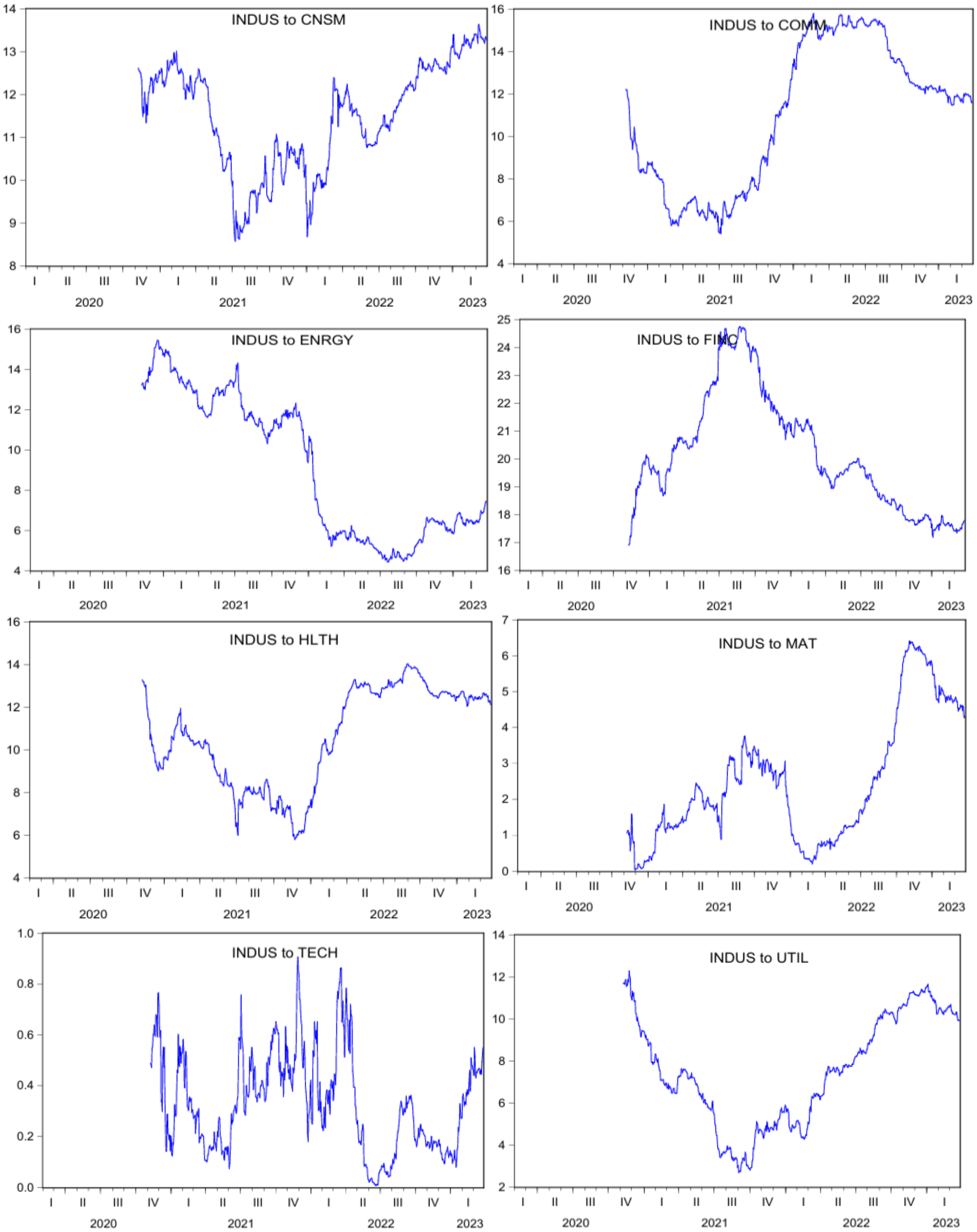
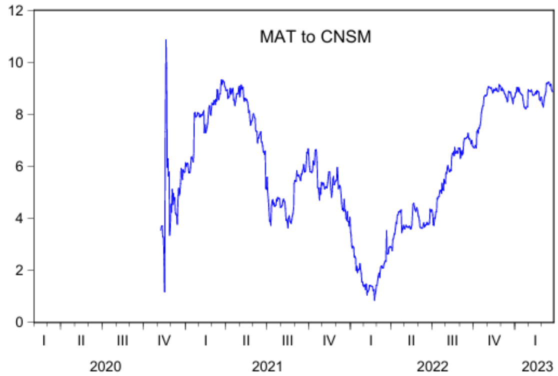
0
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


HLTH to TECH
2.4
2.0
1.6
1.2
0.8
0.4
0.0
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


HLTH to UTIL
14
13
12
11
10
9
8
I II III IV I II III IV I II III IV I
2020
2021
2022
2023


INDUS to CNSM
INDUS to COMM
INDUS to ENRGY
INDUS to FINC
INDUS to HLTH
INDUS to MAT
INDUS to TECH
INDUS to UTIL
2020
2021
2022
2023


MAT to CNSM
0
2
4
6
8
10
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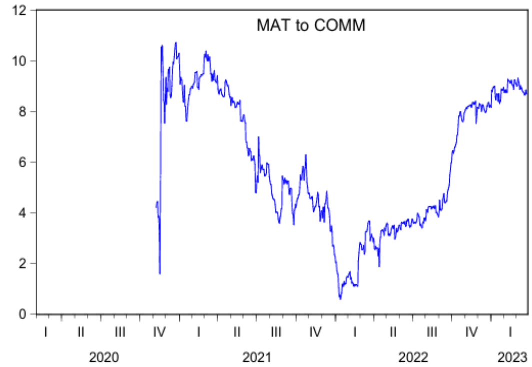
2020
2021
2022
2023


MAT to COMM
0
2
4
6
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2020
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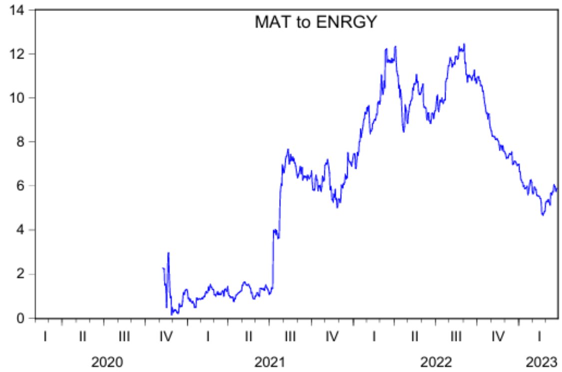
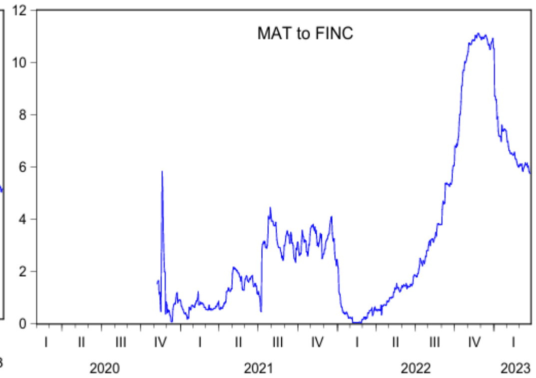
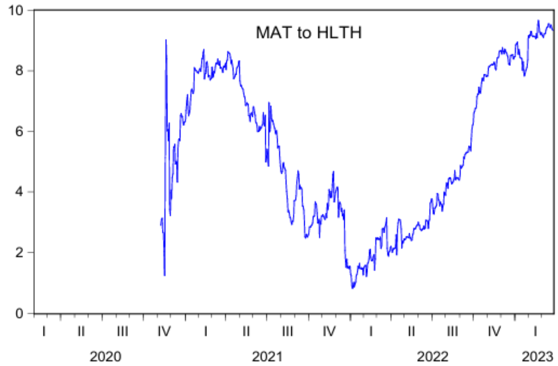
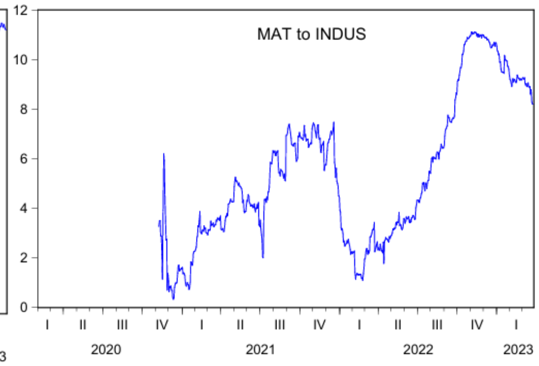
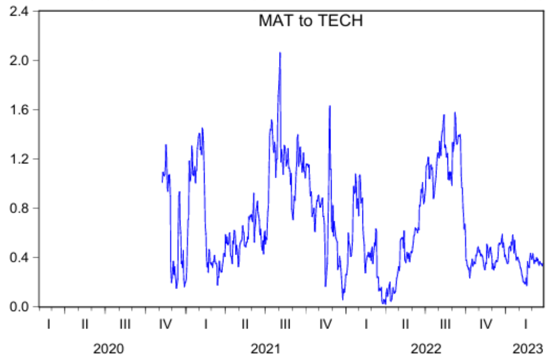
2022
2023

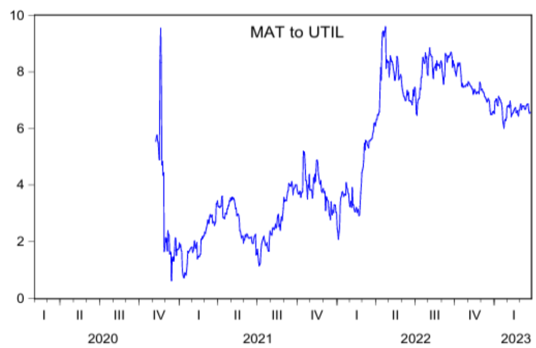

MAT to ENRGY
0
2
4
6
8
10
12
14
2020
2021
2022
2023

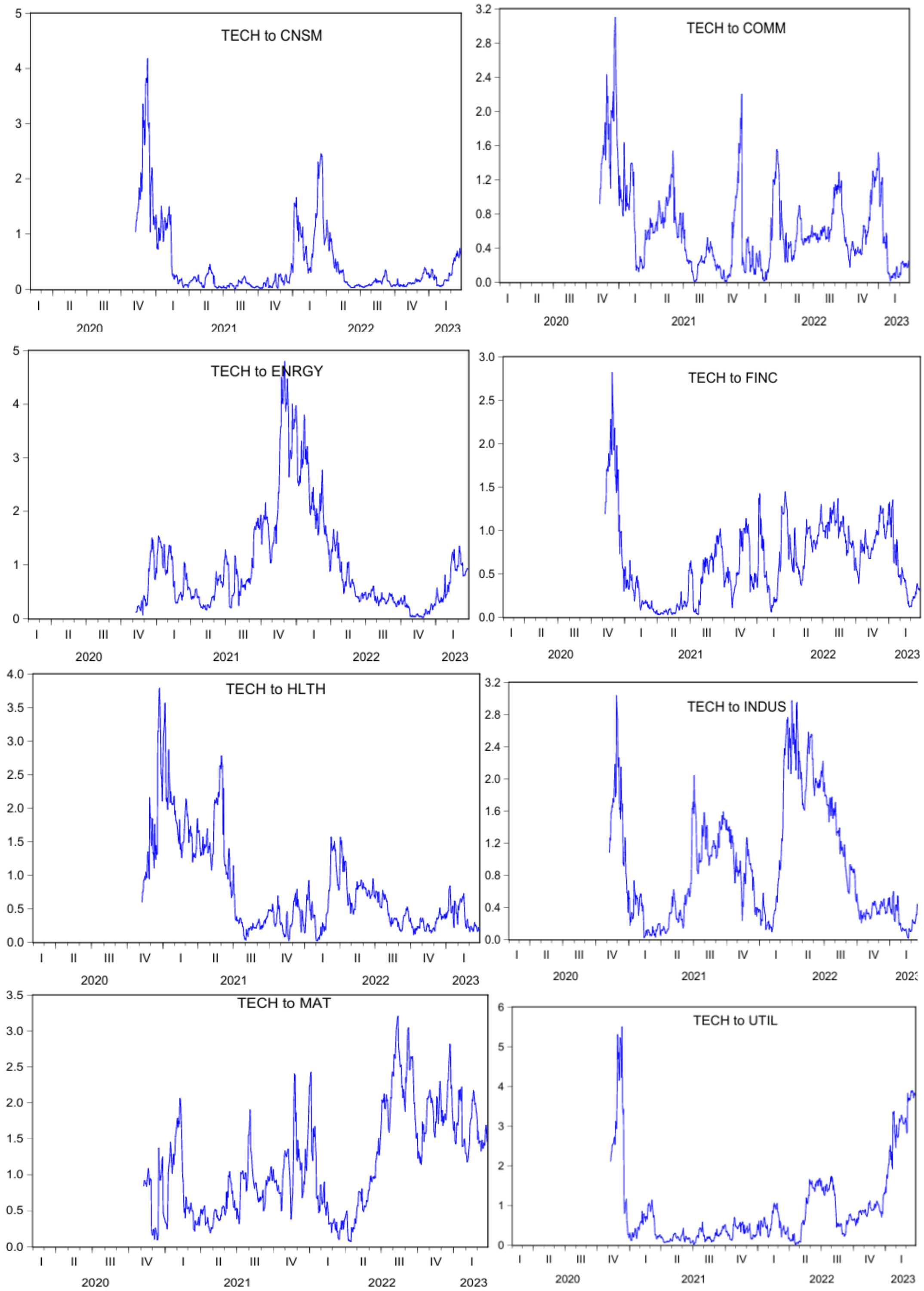

MAT to FINC
0
2
4
6
8
10
12
2020
2021
2022
2023

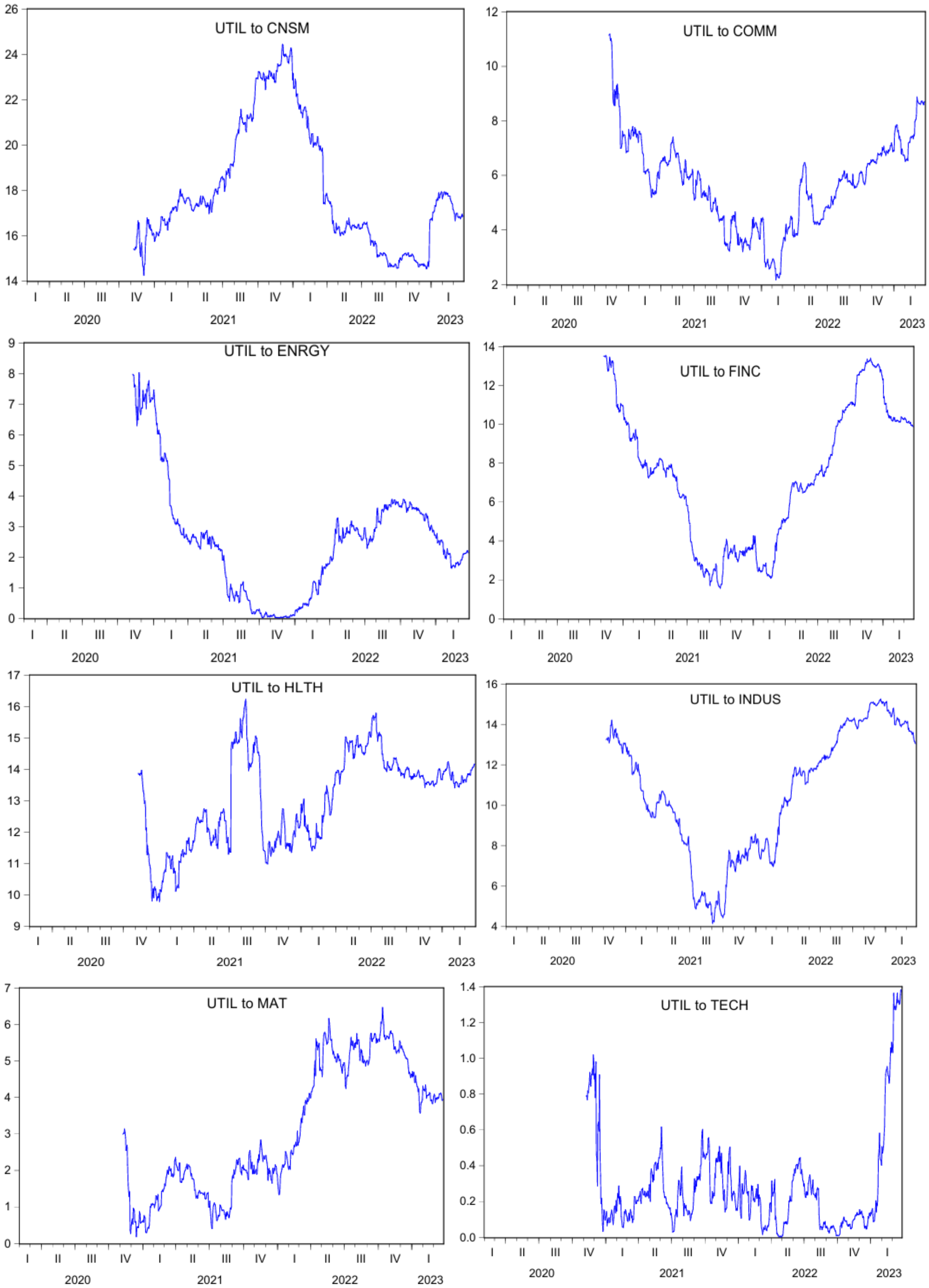

MAT to HLTH
0
2
4
6
8
10
2020
2021
2022
2023


MAT to INDUS
0
2
4
6
8
10
12
2020
2021
2022
2023


MAT to TECH
0.0
0.4
0.8
1.2
1.6
2.0
2.4
2020
2021
2022
2023


MAT to UTIL
0
2
4
6
8
10
2020
2021
2022
2023


TECH to CNSM
TECH to COMM
TECH to ENRGY
TECH to FINC
TECH to HLTH
TECH to INDUS
TECH to MAT
TECH to UTIL
2020
2021
2022
2023


UTIL to CNSM
UTIL to COMM
UTIL to ENRGY
UTIL to FINC
UTIL to HLTH
UTIL to INDUS
UTIL to MAT
UTIL to TECH