SECTORAL CONNECTEDNESS AND RISK SPILLOVERS IN THAILAND'S STOCK MARKET

Sicha Thubdimphun*
Faculty of Economics, Thammasat University,
Bangkok, Thailand
sicha@econ.tu.ac.th

Kittichai Saelee
Faculty of Economics, Thammasat University,
Bangkok, Thailand
kittichai_lee@econ.tu.ac.th

ABSTRACT

Investigating the mechanisms of risk transmission within economic sectors is vital for comprehending the interconnectedness among industries. This study aims to examine the channels of risk propagation by analyzing volatility spillovers within eleven sectors of Thailand's stock market from January 2012 to December 2021. The sectoral volatility is estimated using the ARMA-GARCH technique. The paper utilizes the connectedness measures developed by Diebold and Yilmaz (2009, 2012, 2014) to examine changes in sectoral connectedness and identify significant trends in specific sectors before and during the COVID-19 pandemic. The result is that total volatility connectedness has increased significantly during the COVID-19 pandemic, indicating a significant rise in systematic risk. The Petrochemical and Chemical sector became the largest transmitter during the COVID-19 pandemic. These two findings are consistent with several studies on sectoral connectedness during the COVID-19 situation. In addition, some certain sectors shifted their role from a net transmitter to a net receiver and vice versa. Investors should be aware of the impact of an increase in systematic risk and the switching roles of net transmitters and net receivers when selecting hedging strategies. The Banking sector and the Finance and Security sector did not transmit much volatility to the market. They were net receivers for both the pre-COVID and the COVID periods. The Finance and Security sector was the largest receiver of volatility shocks during the pandemic. This raised concerns about the future stability of Thailand's financial sector. The dynamic analysis using rolling-window estimations yields results consistent with the comparative static analysis. Futhermore, the main results hold true regardless of the window size used for the rolling estimations. Overall, the results of this study contribute to an understanding of the changes in sectoral connectedness and risk spillovers in Thailand's stock exchange as a result of the COVID-19 situation.

Keywords: *ARMA-GARCH, Connectedness, COVID-19, Sectoral connectedness, Stock Exchange of Thailand, Volatility spillovers, VAR*

* corresponding author

1. INTRODUCTION

Financial markets have recently witnessed periods of instability and turmoil. These situations are marked by a high level of unpredictability and can be seen in significant fluctuations in market activity. Volatility is essential to the functioning of financial markets. It serves as a measurement of financial risk or uncertainty surrounding financial asset investment. According to Diebold and Yilmaz (2009, 2012, 2014), total connectedness in securities can be attributed to the level of systematic risk. In addition, though different sectors respond to a shock in different ways, all stock sectors are at least partly interconnected. When there is significant volatility, it might extend to other industries. This process is typically referred to as sectoral spillover or sectoral connectedness, which describes the degree to which various sectors of an economy are interrelated and how changes in one sector influence other sectors. Determining the mechanisms through which risk is transmitted among different sectors in the stock exchange of Thailand could help investors develop better portfolio diversification and hedging strategies, as well as the policymakers select the most effective policy actions.

The outbreak of COVID-19 was one of the major unprecedented events that greatly affected us in many ways. The loss of human lives and the decline in economic activities following the unavoidable lockdown policy are mainly considered to be costly consequences of the pandemic. Much of recent works have attempted to investigate several aspects in which this pandemic has caused the overall and sectoral decline of economic activities. One promising area of focus study is the implication of COVID-19 on the Thai stock market and financial investments. According to the data, the outbreak has resulted in a decline in the overall Thai stock market returns; however, the nature in which the pandemic event affects sectoral volatility returns, as well as the intersectoral linkage aspects of volatility spillovers, has been slightly discussed until now. Our work attempts to fill up the existing gap in the recent Thai literature, and investigate the nature in which COVID-19 affects and reshapes the pattern of sectoral volatility spillovers in the Thai stock markets

Several studies analyzed the impact of the COVID-19 pandemic on sectoral connectedness using stock market data. Choi (2022), Shahzad et al. (2021) Laborda and Olmo (2021) examined the changes in the inter-sectoral volatility linkage in the US stock market due to the COVID-19 pandemic. Bui et al. (2021) investigated the volatilities spillovers across 24 sectors in the Vietnam stock market. Ekinci and Gençyürek (2021) analyzed the shock and volatility spillovers among sectors in the Borsa Istanbul stock exchange. Despite reviewing quite numerous studies on the sectoral volatility spillovers during the COVID-19 pandemic, we have yet to come across any research on the sectoral volatility spillovers for Thailand Stock Exchange. The research on sectoral volatility is quite limited.

This paper examines the volatility connectedness across eleven sectors of the Stock Exchange of Thailand. There are two periods of analysis, the pre-COVID period (January 2012 – December 2019) and the COVID period (January 2020 – December 2021). The objectives of our paper are two folds. Firstly, within the sectoral analysis of 11 sectors of the Thai stock market, we attempt to uncover the key sector that contributes most to the volatility spillover in the Thai stock market. Second, we ask if the COVID-19 epidemic has changed the nature of financial connectedness. The ARMA-GARCH technique was used to measure sectoral volatilities. After that, we utilize the VAR techniques developed by Diebold and Yilmaz (2009, 2012, 2014, 2015) to estimate the sectoral volatility connectedness. In line with many studies (Laborda and Olmo (2021), Bui et al.(2022), Shahzad et al. (2021), Ekinci and Gençyürek (2021)), we found that total sectoral volatility connectedness significantly increased during the

COVID-19 pandemic as compared to before. The systematic risk in the stock exchange of Thailand was much higher because of the situation. In addition, the Petrochemical and Chemical industry became the primary sector through which volatility was transmitted to the other sectors. This result is consistent with Ahmad et al. (2021), Choi (2022), Costa et al. (2022), and Laborda and Olmo (2021). Besides, we found that the Finance and Security sector became the main receiver of the shocks during the pandemic period. The financial industry was the receiver throughout both periods of the study. This result coincides with Laborda and Olmo (2021). Since the instability of financial institutions can cause a financial crisis, this finding suggests policymakers should monitor financial institutions constantly. Moreover, there was evidence of role-switching from a transmitter to a receiver and from a receiver to a transmitter. The pandemic caused a structural change. It might be too soon to find out whether this structural change is temporary or permanent. Investors should be aware of this structural change when choosing hedging strategies.

The remainder of this paper is organized as follows. Section 2 describes the Research methodology and the data. Section 3 presents the quantitative results. Section 4 discusses several critical results and policy implications, while section 5 concludes.

2. RESEARCH METHODOLOGY AND DATA

2.1. Research Methodology

In this paper, we study the *systematic spillover effect* among sectoral financial activities using the framework developed by Diebold and Yilmaz (2014). Our work slightly departs from their original work in that we focus on the connectedness among *sectoral volatilities returns (hereafter, sectoral volatilities)*; the original study by Diebold and Yilmaz focused on the connectedness of firms through the lenses of firms' returns. Putting their framework in our contextual application, we proceed with the following four steps.

First, we study the behavior of sectoral returns, denoted by $\boldsymbol{r_{i,t}}$, using the ARMA-GARCH(1,1) model. Then, we uncover the implied sectoral volatilities ($\boldsymbol{\sigma_{i,t}^2}$) from each of the estimated models. *Second*, we analyze the structural relationship among the sectoral volatilities using the Vector Autoregression (VAR) framework. For illustration, we assume that sectoral volatilities are interlinked by the following VAR presentation,

$$Y_t = C + A_1 * Y_{t-1} \dots + A_P * Y_{t-P} + B * e_t$$

where C is a vector of constants with order K, $Y_t' = \begin{bmatrix}\sigma_{1,t}^2 & \dots & \sigma_{K,t}^2\end{bmatrix}$ denotes the collection of sectoral volatilities for each of the K sector and e_t represents the volatilities shocks that must be structurally identified. Our VAR model is estimated by the Maximum likelihood method.

Third, given the estimated VAR model, the structural shocks (e_t) are econometrically identified. We follow the recent literature and identify the shocks using the generalized impulse response function techniques developed by Koop et.al.(1996), and Persarran and Shin (1998). This method has an advantage over other existing identification methods in that the results are invariant to the ordering assumption among structural shocks. *In the final step*, we compute the h-step ahead forecast error variance decomposition (FEVD) of the volatility in sector-i that is attributed to volatility shocks in sector-j. Having defined the pairwise FEVD object as d_{ij}, we then calculate the key connectedness measures proposed by Diebold and Yilmaz (2014), including (i) “TO-connectedness ($T_{\cdot\leftarrow i}$)”, (ii) “FROM-connectedness ($F_{i\leftarrow\cdot}$)” and (iii) “NET-connectedness (N_i)”. These measures are summarized in the table 1.

2.2. Data

This paper analyzes the daily data of 11 sector indices in the Stock Exchange of Thailand from January 2012 to December 2021 (2610 trading day observations). The series is divided into two periods; the pre-COVID period and the COVID period. The pre-COVID period is from January 2012 to December 2019 (2087 trading day observations). The pre-COVID period starts on January 2012. This starting date is chosen because Thailand's financial stability prior to 2012 was affected by massive flooding. The COVID period is from January 2020 to December 2021 (523 trading day observations). It is assumed that the COVID period begins on January 2020 because the cases of pneumonia in Wuhan, China were first reported by WHO on December 31, 2019. The 11 sectors in the Stock Exchange of Thailand include Automobile(AUTO), Banking(BANK), Commerce (COMMERCE), Construction Materials (CONS), Fashion (FASHION), Insurance (INSUR), Packaging (PACKAGE), Finance and Securities (FINANCE), Food and Beverages (FOOD), Petrochemicals and Chemicals (PETRO), and Tourism and Leisure (TOURISM). The data is obtained from Thompson Reuters DataStream International.

Table 1: Sectoral connectedness matrix
(Source: Adapted from Diebold and Yilmaz (2014))

	$\boldsymbol{\sigma^2_{1,t}}$	$\boldsymbol{\sigma^2_{2,t}}$	...	$\boldsymbol{\sigma^2_{K,t}}$	**FROM others**
$\boldsymbol{\sigma^2_{1,t}}$	d_{11}	d_{12}	...	d_{1K}	$F_{1\leftarrow\cdot} = \sum_{j\neq 1} d_{1j}$
$\boldsymbol{\sigma^2_{2,t}}$	d_{21}	d_{22}	...	d_{2K}	$F_{2\leftarrow\cdot} = \sum_{j\neq 2} d_{2j}$
$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$
$\boldsymbol{\sigma^2_{K,t}}$	d_{K1}	d_{K2}	...	d_{KK}	$F_{K\leftarrow\cdot} = \sum_{j\neq K} d_{2j}$
TO others	$T_{\cdot\leftarrow 1} = \sum_{i\neq 1} d_{i1}$	$T_{\cdot\leftarrow 2} = \sum_{i\neq 2} d_{i2}$	...	$T_{\cdot\leftarrow K} = \sum_{i\neq 2} d_{iK}$	$\frac{\sum_{i\neq j} d_{ij}}{K}$
NET	$N_1 = T_1 - F_1$	$N_2 = T_2 - F_2$	...	$N_K = T_K - F_K$	

3. QUANTITATIVE RESULTS

3.1 The ARMA-GARCH(1,1) results

The ARCH and GARCH models are widely used to measure the volatility of stock returns and provide a good starting point for the volatility analysis. What are presented in tables 2 and 3 are the variance equation estimation results of the GARCH (1,1) for the pre-COVID and the COVID periods, respectively. Each equation is estimated with the Maximum likelihood under the assumption that the distribution function of error terms is governed by Students-T.

From table 2 and table 3, all estimated coefficients of variance equation (ARCH and GARCH coefficients) are significant at 10%; the results hold true under both sub-sample analyses. Moreover, the sums of the two coefficients associated with the volatility’s equations (alpha + beta) are lower than one; the GARCH(1,1) estimations are stationary and stable. Given our simple diagnostic checking methods, we have detected no signs of unusual results.

Table 2: Market Volatility of 11 Sectors in the Stock Exchange of Thailand using GARCH(1,1) estimating, the Pre-COVID Period: January 2012 – December 2019

Variance Equation	**AUTO**	**BANK**	**COMMERCE**	**CONS**	**FASHION**	**FINANCE**
Arch (alpha)	0.1465*** (0.0325)	0.0551*** (0.0100)	0.0901*** (0.0158)	0.0397*** (0.0088)	0.1008*** (0.0197)	0.1464*** (0.0241)
Garch (beta)	0.7569*** (0.0001)	0.9422*** (0.0096)	0.9005*** (0.0154)	0.9512*** (0.0105)	0.8520*** (0.0231)	0.8231*** (0.0234)
Constant	1.02 ($\times10^{-5}$)*** (1.46 ($\times10^{-4}$))	7.52 ($\times10^{-7}$)** (3.47($\times10^{-7}$))	1.67($\times10^{-6}$)** (5.79($\times10^{-7}$))	1.12($\times10^{-6}$)** (4.87($\times10^{-7}$))	2.41($\times10^{-6}$)*** (5.91($\times10^{-7}$))	7.69($\times10^{-6}$)*** (1.86($\times10^{-6}$))
alpha + beta	0.9034	0.9974	0.9906	0.9910	0.9528	0.9695
Variance Equation	**FOOD**	**INSURE**	**PACKAGE**	**PETRO**	**TOURISM**	
Arch (alpha)	0.0972*** (0.0177)	0.0571*** (0.0123)	0.2134*** (0.0426)	0.0612*** (0.0109)	0.0380*** (0.0084)	
Garch (beta)	0.8642*** (0.0220)	0.9232*** (0.0123)	0.6869*** (0.0467)	0.9295*** (0.0122)	0.9577*** (0.0088)	
Constant	3.63($\times10^{-6}$)*** (1.02($\times10^{-6}$))	1.84($\times10^{-6}$)*** (6.85($\times10^{-7}$)	1.64($\times10^{-6}$)*** (3.70($\times10^{-6}$))	2.78($\times10^{-6}$)** (1.11($\times10^{-6}$))	9.71($\times10^{-7}$)** (4.60($\times10^{-7}$))	
alpha + beta	0.9615	0.9803	0.9004	0.9907	0.9957	

Notes: Standard errors are in parentheses. Superscripts *, **, and *** denote the significance at 10 percent, 5 percent, and 1 percent confidence levels, respectively.

Table 3: Market Volatility of 11 Sectors in the Stock Exchange of Thailand using GARCH(1,1) estimating, the COVID Period: January 2020 – December 2021

Variance Equation	**AUTO**	**BANK**	**COMMERCE**	**CONS**	**FASHION**	**FINANCE**
Arch (alpha)	0.2078** (0.0938)	0.0653** (0.0310)	0.0695*** (0.0269)	0.0730*** (0.0260)	0.1406** (0.0566)	0.1406*** (0.0469)
Garch (beta)	0.6533*** (0.0003)	0.9168*** (0.0314)	0.8918*** (0.0397)	0.8970*** (0.0317)	0.6868*** (0.1195)	0.7984*** (0.0545)
Constant	2.14($\times10^{-5}$)** (3.40($\times10^{-4}$))	1.48($\times10^{-5}$) (9.31($\times10^{-6}$))	5.95($\times10^{-6}$)* (3.36($\times10^{-6}$))	5.01($\times10^{-6}$)*** (2.68($\times10^{-6}$))	1.09($\times10^{-6}$)** (5.24($\times10^{-6}$))	2.22($\times10^{-6}$)** (9.93($\times10^{-6}$))
alpha + beta	0.8612	0.9822	0.9614	0.9700	0.8274	0.9390
Variance Equation	**FOOD**	**INSURE**	**PACKAGE**	**PETRO**	**TOURISM**	
Arch (alpha)	0.0890*** (0.0301)	0.1629** (0.0658)	0.0851** (0.0412)	0.0653*** (0.0200)	0.0286** (0.0140)	
Garch (beta)	0.9047*** (0.0255)	0.6531*** (0.0658)	0.9138*** (0.0327)	0.9258*** (0.0198)	0.9709*** (0.0137)	
Constant	2.14($\times10^{-6}$) (1.32($\times10^{-6}$))	2.69($\times10^{-5}$)** (1.16($\times10^{-5}$))	6.68($\times10^{-6}$) (5.32($\times10^{-6}$))	4.08($\times10^{-6}$) (3.06($\times10^{-6}$))	1.62($\times10^{-6}$)* (2.43($\times10^{-6}$))	
alpha + beta	0.9937	0.8160	0.9989	0.9910	0.9995	

Notes: Standard errors are in parentheses. Superscripts *, **, and *** denote the significance at 10 percent, 5 percent, and 1 percent confidence levels, respectively.

3.2. Comparative Static Analyis of the Spillovers Effects Across 11 Sectors in the Stock Exchange of Thailand

3.2.1 Pre-COVID connectedness

Against the backdrop of pre-COVID periods, large fractions of each sectoral volatilities are found to have been mainly captured by their own volatility shocks. As reported in table 4 below, the diagonal elements represent the own-shocks effect; the figures range from the lowest value of 35.90% in FOOD industry to the highest one of 81.41% in FASHION industry. This implies that both sectors are those having the highest and lowest value of FROM-connectedness measures ($F_{i\leftarrow\cdot}$), respectively. In particular, we found that the average FROM-connectedness measures, or overall spillovers index, is roughly around 50.32.

To gauge the impact of the sector-i volatility shocks on the volatility of other related sectors, consider the figures reported in *row 12* of table 4. FOOD industry has the highest TO-connectedness ($T_{\cdot\leftarrow i}$) of 82.82 meanwhile FASHION industry has the least reporting figure of 9.64. To measure the net spillover effect of each sectoral volatility shocks, the net effect of directional connectedness measures is more informative; the measures are reported in row 13. From the study, we found that PACKAGE sector plays the most important role as the largest net transmitter to the financial network; meanwhile PETRO industry is the biggest net receiver from other related sectors.

3.2.2 Connectedness during the COVID periods

With the outbreak of COVID-19, there had been several changes in the nature for which sectoral volatility shocks play role in generating sectoral connectedness. Each sectoral volatility is found to have been less explained by their own volatility shocks. As reported in table 5 below, the diagonal elements represent the own-shocks effect; the figures range from the lowest value of 35.90% in FOOD industry to the highest one of 49.54% in FASHION industry. When compared with the same reporting values, the figures drop significantly from those in the pre-COVID periods. On the other hand, this implies that the cross-effect of volatility shocks has increased significantly. The FROM-connectedness measures ($F_{i\leftarrow\cdot}$) rise in all sectors, with the most notable feature being that the average FROM-connectedness measures, or overall spillovers index, was around 75.94.

The impact of the sector-i volatility shocks on other related sectoral volatilities also increased during the COIVD periods. Consider the figures reported in *row 12* of table 5. PETRO industry has the highest TO-connectedness ($T_{\cdot\leftarrow i}$) of 154.02 meanwhile PACKAGE industry has the least reporting figure of 24.90. Both minimum and maximum values are higher than those counterparts observed before the COVID period. For the net effect of directional connectedness, the reporting measures in row 13 suggest that PETRO sector plays the most important role as the largest net transmitter to the connectedness among sectoral volatilities; meanwhile, TOURISM industry is the biggest net receiver from other related sectors.

Table 4: The Market Volatility Spillovers of 11 Sectors in the Stock Exchange of Thailand, the Pre-COVID Period: January 2012 – December 2019

	AUTO	BANK	COM MERCE	CONS	FASHI ON	FIN-ANCE	FOOD	IN-SURE	PACK -AGE	PE-TRO	TOUR -ISM	FROM
AUTO	48.56	3.29	3.89	3.12	2.06	7.11	9.12	6.00	11.51	1.57	3.78	**51.44**
BANK	3.85	41.33	6.33	8.96	0.47	5.77	9.89	8.75	5.94	4.63	4.08	**58.67**
COM-MERCE	4.52	7.47	47.01	6.01	0.44	4.19	12.22	8.45	4.63	1.53	3.51	**52.99**
CONS	6.36	8.75	5.30	39.89	0.55	5.87	8.73	7.07	7.52	4.60	5.36	**60.11**
FASH-ION	4.19	0.60	0.75	0.65	81.41	1.28	2.38	0.90	6.85	0.53	0.47	**18.59**
FIN-ANCE	8.10	3.07	3.52	4.53	0.90	48.60	9.49	6.77	8.49	1.61	4.92	**51.40**
FOOD	6.06	6.85	11.56	7.31	1.37	7.06	35.90	7.78	9.20	2.22	4.68	**64.10**
INSURE	8.85	5.30	6.60	4.59	0.60	4.04	8.30	48.79	7.93	1.68	3.33	**51.21**
PACK-AGE	9.88	4.07	2.48	5.52	2.14	7.11	9.59	7.26	45.80	2.13	4.03	**54.20**
PETRO	4.45	5.99	2.19	5.49	0.88	3.11	5.11	3.93	10.79	54.85	3.19	**45.15**
TOUR-ISM	3.47	3.41	2.91	5.90	0.25	7.12	7.99	6.66	6.91	1.08	54.30	**45.70**
TO	**59.72**	**48.81**	**45.54**	**52.09**	**9.64**	**52.66**	**82.82**	**63.58**	**79.77**	**21.59**	**37.35**	**50.32**
NET	**8.28**	**-9.86**	**-7.45**	**-8.03**	**-8.95**	**1.25**	**18.72**	**12.37**	**25.57**	**-23.56**	**-8.35**	

Table 5: The Market Volatility Spillovers of 11 Sectors in the Stock Exchange of Thailand, the COVID Period: January 2020 – December 2021

	AUTO	BANK	COM MERCE	CON S	FASHI ON	FIN-ANCE	FOOD	IN-SURE	PACK -AGE	PE-TRO	TOUR -ISM	FROM
AUTO	49.59	6.40	9.25	2.50	5.42	1.62	6.78	5.10	1.35	7.77	4.23	**50.41**
BANK	7.04	22.44	8.31	3.78	8.64	3.56	11.52	13.00	2.43	15.98	3.31	**77.56**
COM-MERCE	3.41	4.75	19.50	6.80	4.43	5.97	18.74	13.12	2.65	17.30	3.33	**80.50**
CONS	2.86	4.27	9.79	10.99	5.37	7.10	18.39	16.71	4.44	17.92	2.16	**89.01**
FASH-ION	3.31	3.77	9.06	4.24	35.22	3.67	12.38	11.45	4.46	11.64	0.80	**64.78**
FIN-ANCE	2.10	5.36	10.66	8.59	4.39	10.76	18.09	15.23	5.29	17.42	2.11	**89.24**
FOOD	3.09	5.14	12.43	6.31	3.40	6.27	19.76	17.23	3.87	20.26	2.23	**80.24**
INSURE	4.58	5.91	10.06	5.67	3.58	5.79	14.92	25.94	3.89	16.96	2.68	**74.07**
PACK-AGE	6.85	4.86	8.94	5.79	4.81	4.41	13.88	12.35	23.30	12.87	1.95	**76.70**
PETRO	3.08	6.44	10.93	5.41	3.89	4.33	17.01	18.35	3.13	25.34	2.09	**74.66**
TOUR-ISM	8.44	5.19	11.22	4.06	4.62	3.37	11.77	11.04	2.61	15.90	21.78	**78.22**
TO	**44.76**	**52.08**	**100.65**	**53.16**	**48.53**	**46.10**	**143.48**	**133.58**	**34.13**	**154.02**	**24.90**	**75.94**
NET	**-5.65**	**-25.48**	**20.14**	**-35.85**	**-16.25**	**-43.14**	**63.25**	**59.52**	**-42.57**	**79.36**	**-53.32**	

3.3 Dynamic Analysis

In the previous part, this paper analyzes the static measurement of sectoral connectedness of the pre-COVID and the COVID-19 periods. This section focuses on the dynamics of the volatility connectedness overtime. A dynamic index, as advocated by Diebold and Yalmiz (2012), can be alternatively used to investigate the impact of COVID-19 on Thailand's Stock market connectivity. The index derives a time variation of the spillover measure using a rolling-windows VAR estimation of the counterparts' static connectivity index described in the section 2 above. With the baseline 180-day rolling-windows VAR estimates and 12-day horizon forecast-error variance decomposition, below presents the estimation results.

3.3.1 Dynamic total connectedness

Figure 1 illustrates changes in the overall connectedness between 2012 and 2021. The graph demonstrates that the level of total connectedness varies over time and ranges from 29.3 to 90.85. Notably, during the COVID-19 period, the total connectedness considerably increased compared to the preceding two years. Analyzing the dynamic total connectedness reveals a sharp spike, with the total connectedness indeks increased from 47.69 on February 21, 2020, to 68.9 on February 24, 2020. This upward trend continued until the total connectedness index reaches its peak of 90.85 on March 13, 2020. The average total connectedness during the pre-COVID period was 56.11, while the figure during to COVID-19 period was 68.71. The results for 60, 120, 240, 360 days rolling windows show this similar pattern. This finding is in line with the previous section, as we observed a similar trend. Specifically, we found that there was a substantial increase in overall connectedness during the COVID-19 period.

Figure 1: Total Connectedness (180-days rolling-sample windows) during 2012 – 2021

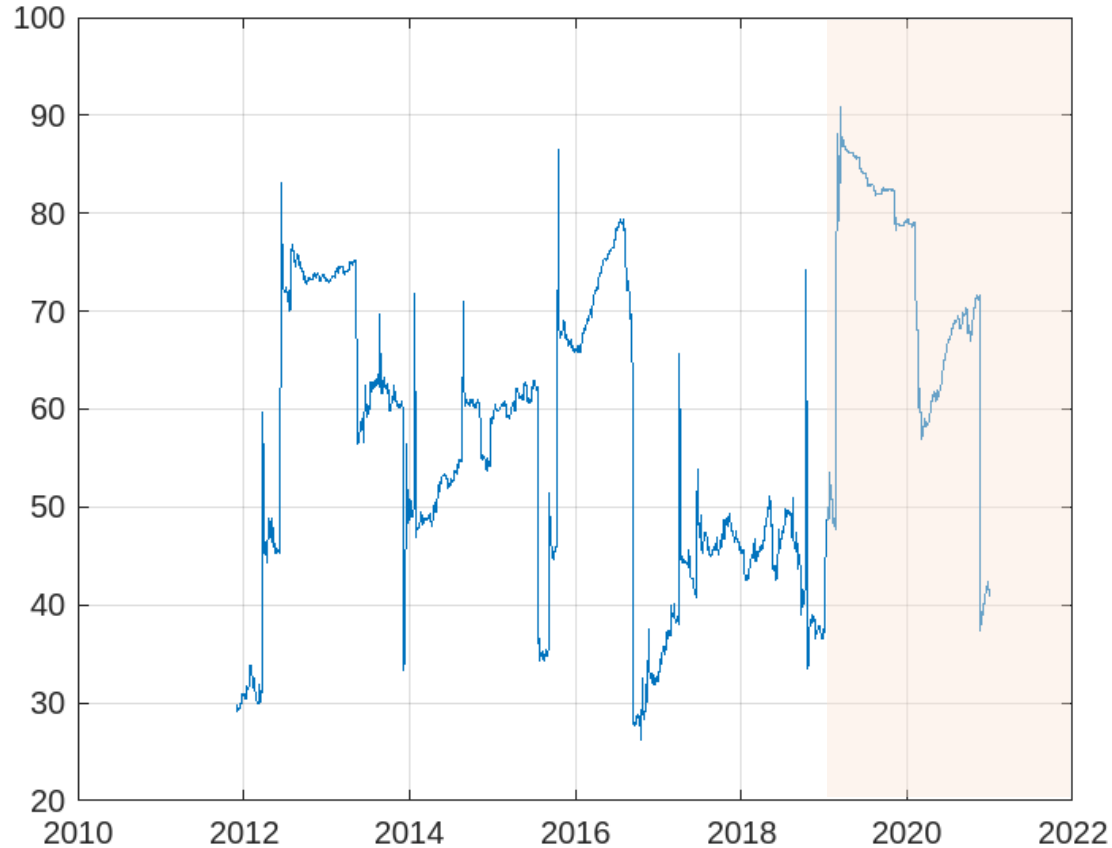


Figure 2: To-Connectedness (180-days rolling-sample windows) during 2012 – 2021

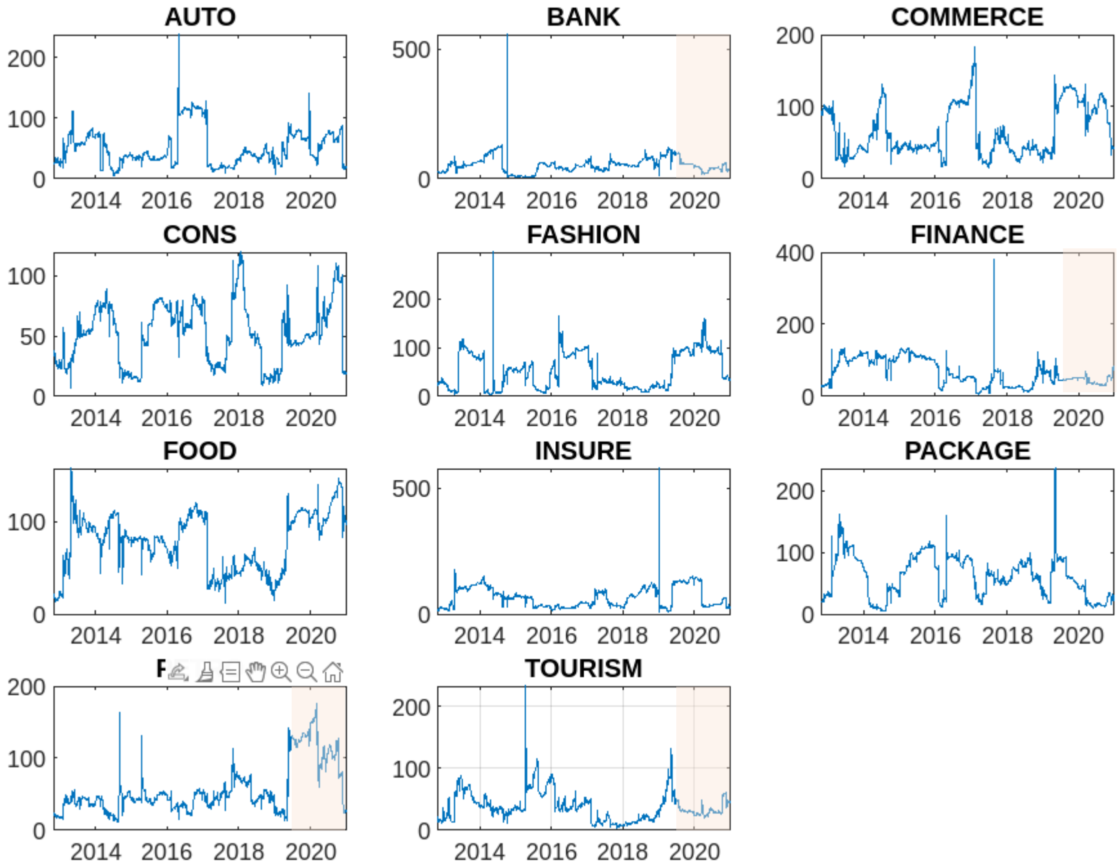


Figure 3: From-Connectedness (180-days rolling-sample windows) during 2012 – 2021

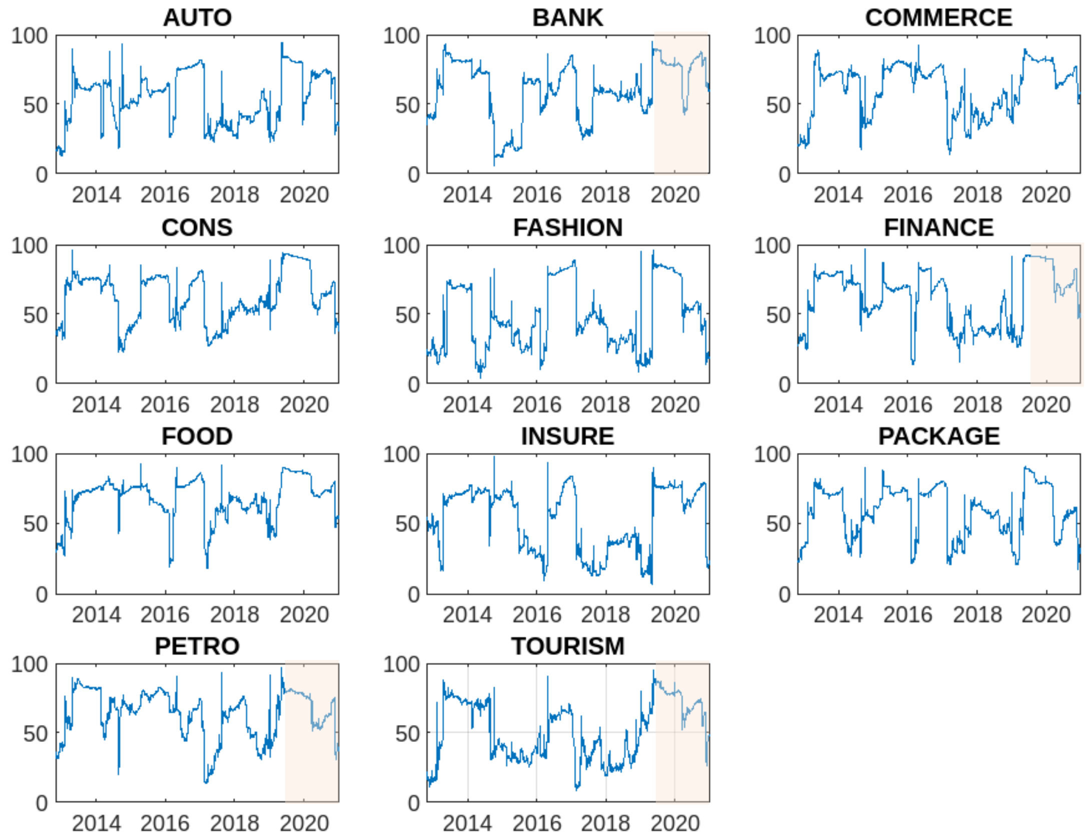
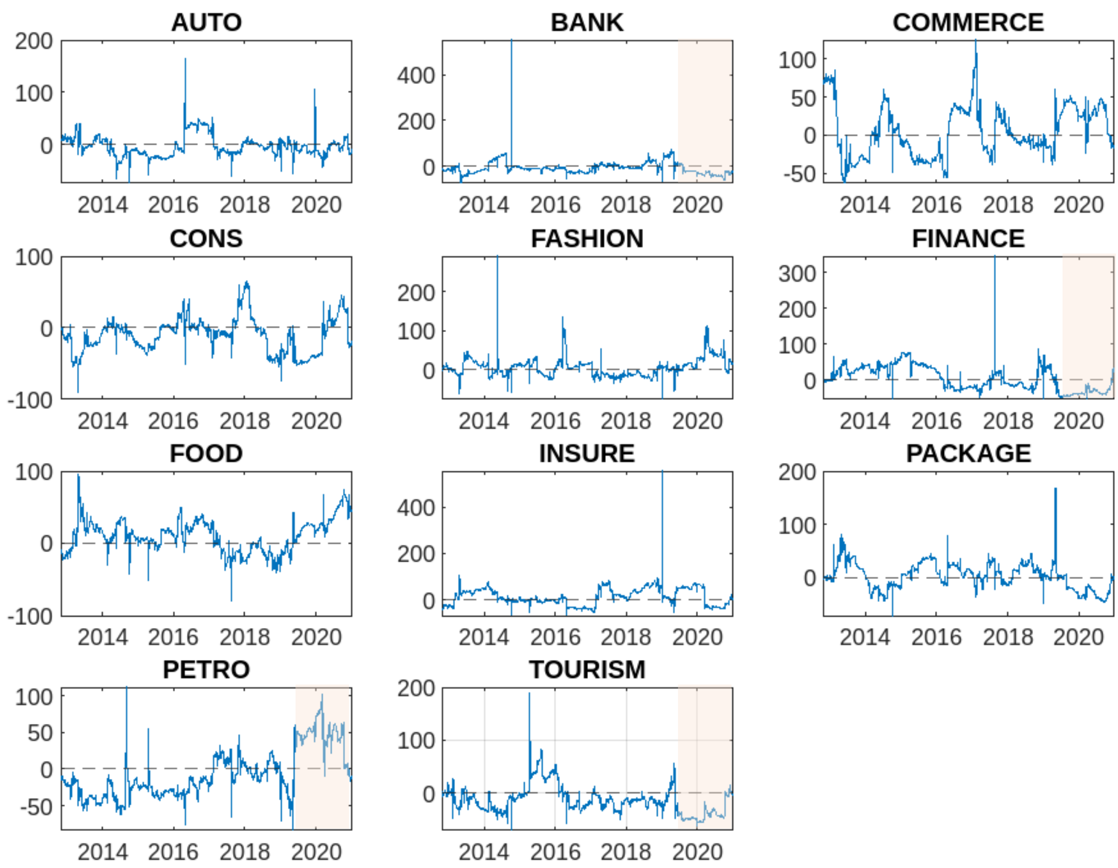


Figure 4: Net Connectedness (180-days rolling-sample windows) during 2012 – 2021



3.3.2 Dynamic sectoral volatility connectedness

Figures 2, 3, and 4 respectively display changes in the To-, From-, and Net-connectedness respectively for each of the 11 sectors during the period of 2012-2021. All the three connectedness indices exhibit variation over time.

Upon analysis, we investigated the level of Net-connectedness and discovered intriguing patterns that resembled those observed in the previous session. Notably, the BANK sector was identified as a minor recipient of shocks most of the time prior to the onset of COVID-19. However, during the pandemic, the BANK sector experienced a substantial increase in the size of net volatility shocks it received from other sectors. The role of the FINANCE sector varied across time; however, during the COVID-19 period, it became the net-receiver from the very beginning of COVID-19 until the end of 2021. Similarly, the role of the TOURISM sector also varied over time, but it remained a net receiver throughout the entire pandemic period. Prior to the COVID-19 period, its prominent role was as a net receiver most of the time. Notably, during the COVID-19 period, the PETRO industry became a big net transmitter.

Next, we observed the level of To-connectedness. Notably, the PETRO industry's To-connectedness index increased substantially during the pandemic period. In contrast, the BANK, FINANCE, and TOURISM industries' To-connectedness levels were relatively similar to their pre-pandemic levels.

Turning to the From-connectedness, we found that the BANK, FINANCE, and TOURISM sectors' From-connectedness increased during the COVID-19 period. In contrast, the PETRO sector's From-connectedness index remained relatively stable compared to the pre-COVID period.

3.3.3 Robustness check

We conduct additional robustness tests to explore the sensitivity of the computed dynamic index during the course of the rolling-windows sample utilized in the VAR estimation. In other words, we re-estimate the index using five alternative sample periods: 60-day, 120-day, 180-day, 240-day, and 360-day. Our findings reveal that each form of related index is in line with one another. Therefore, the main conclusion, as found in sections 3.3.1 and 3.3.2, remains unchanged.

4. DISCUSSION AND IMPLICATION

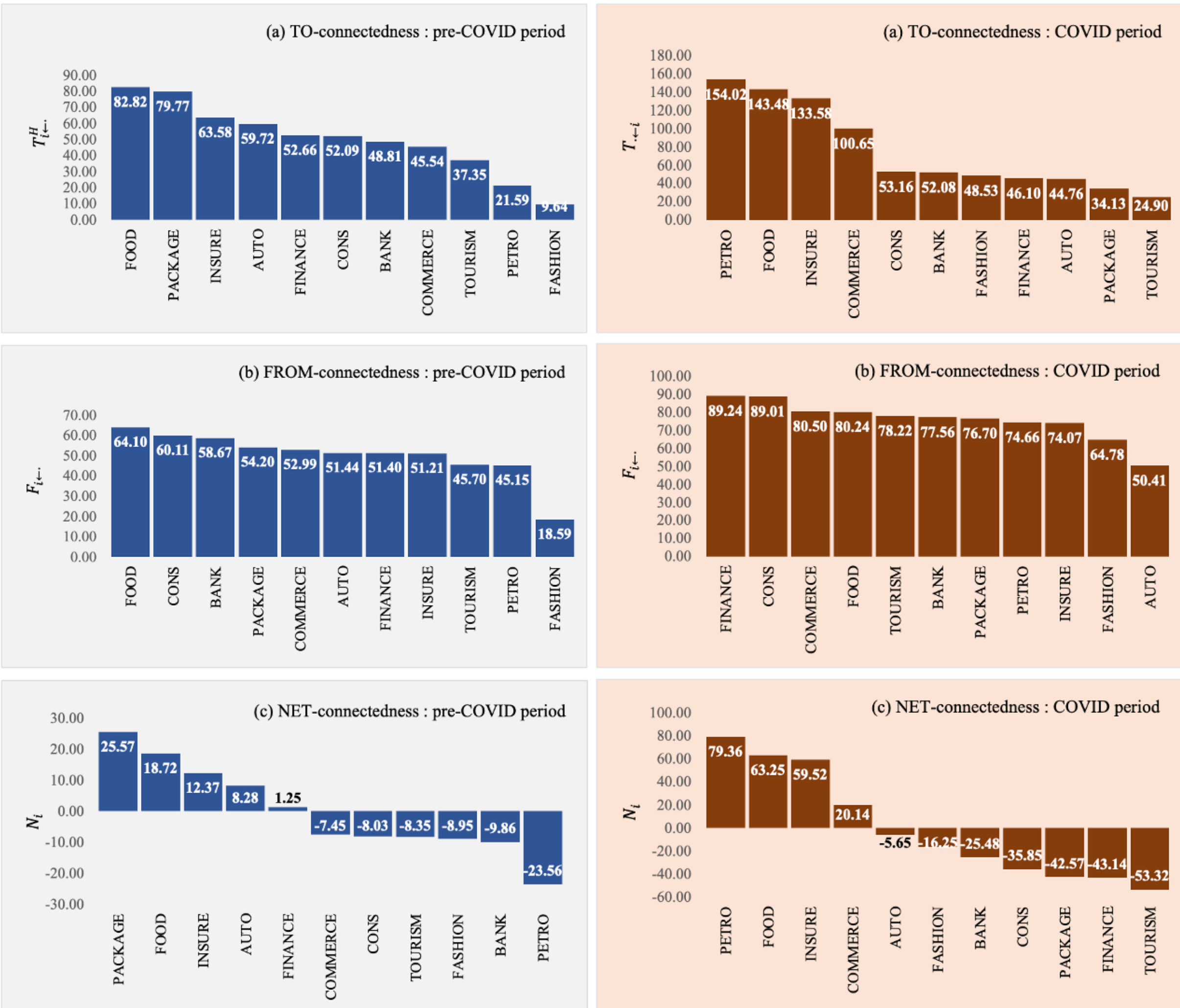
There are several noteworthy points about sector connectedness, and some of them will be highlighted in this session. Overall, the total connectedness in the COVID period, 75.94, is significantly higher than the pre-COVID period 50.32. This increase in total connectedness may imply a rise in systematic risk. The degree of connectedness is related to systematic risk. Risks that are not connected can be diversified, and as a result, cannot be systematic. Many on sectoral connectedness studies (Bui et al.(2022), Ekinci and Gençyürek (2021), Laborda and Olmo (2021), Shahzad et al. (2021)) also found that total connectedness increased sharply during the COVID-19 pandemic.

To further examine the sector's interconnectedness, the graphs in figure 5 display the FROM-connectedness, TO-connectedness, and NET-connectedness in descending order. There are structural changes in the patterns of volatilities spillovers across sectors.

As depicted in figure 5a, the Petrochemicals and Chemicals sector was the second lowest transmission of shocks to other sectors in the market, but during the pandemic, it had the strongest volatility spillover effects on other sectors. This result is in line with Ahmad et al. (2021), Choi (2022), Costa et al. (2022), and Laborda and Olmo (2021), which studied the volatilities spillovers across industries in the US stock market. A possible explanation is that the Petroleum and Chemicals sector is most affected by the pandemic shocks (Baek et al. (2020)). The Petrochemicals and Chemical sectors provide petro oil and other chemicals which are the main input for all other sectors. In addition, this result aligns with Hongsakulvasu et al. (2020), which found that the impact of Singapore's oil market on Thailand's sectoral return was greater than it was before the outbreak of COVID-19. Banking and Finance and Securities do not transmit much volatility to the market both during the pre-COVID period and the COVID period.

Figure 5b presents the ranking of the FROM-connectedness of all eleven sectors. Before the COVID pandemic, the Finance and Securities sector was not among the sectors with the highest FROM-connectedness. However, the Finance and Securities sector became the major receiver of the volatility shocks sent from the market during the COVID pandemic. This result aligns with the finding of Panyagometh (2020). The possible reason is that the COVID pandemic has had a significant negative impact on the financial position of the private sector, specifically the business and household sectors, which are the primary clients of the financial sector. This is particularly true for finance and securities companies that primarily serve retail customers. The Food and Beverage sector, on the other hand, had the highest FROM-connectedness before the pandemic but was not one of the major receivers during the pandemic. Even though all industries were negatively affected by the situation, it might be possible that the Food and Beverage sector was relatively affected less by the shocks from other sectors. The demand for food and beverage is usually steady, and it is not significantly affected by shocks in the market or external factors as much as other sectors in the economy due to its nature of necessities.

Figure 5: Ranking Plots of (a) TO-connectedness $T_{\cdot\leftarrow i}$ (b) FROM-connectedness $F_{i\leftarrow\cdot}$, and (c) NET-connectedness N_i : A comparison between pre-COVID period and COVID period (Source: author's calculation)



The graphs of the NET-connectedness for every 11 sectors are plotted in figure 5c. The role of certain sectors has shifted. A sector that transmits more (less) shocks to other sectors in the market than receives from them is considered a transmitter (receiver). During the COVID pandemic, the Automobile, Finance and Securities, and Packaging sectors have switched their roles from a transmitter to a receiver. Conversely, the Commerce and Petrochemicals and Chemicals sectors have experienced a shift in their role from being a receiver to being a transmitter. The Tourism and Leisure sector became the largest receiver of the shocks (-53%). It is unclear if the changes in sectoral connectedness during the Covid pandemic are temporary or permanent. It is possible that some parts of the effect can be long-lasting. Investors should be aware of the change in the risk spillover pattern that happened during the COVID situation. The tourism industry has been heavily impacted by the COVID pandemic due to travel restrictions and social-distancing policy. However, this paper found that the other sectors in the market did not receive much volatility shocks from the Tourism and Leisure sector. This finding is in line with Ekinci and Gençyürek (2021)'s research on the Borsa Istanbul stock exchange.

Furthermore, the Banking and the Finance and Security sectors are the net receivers of the volatility shocks both before the COVID and during the COVID period. The COVID situation is different from the financial crisis, in which the shocks began and spread from the Banking and Finance and Securities sectors. It is possible that the COVID shocks, on the other hand, directly impacted the real sectors and then the volatility shocks were transmitted to the financial sector. This result aligns with Laborda and Olmo (2021), who found that the banking and insurance sectors were the source of volatility risk during the 2007-2009 global financial crisis while the energy and technology sectors were the main transmitter of volatility shocks during the COVID situation. Following the COVID incident, this evidence may cause alarm in the future stability of Thailand's financial sector. Volatility shocks transmitted from non-financial sectors to the financial sector in the stock market may signify risk transfer from the real sector to the financial sector. Hence, even after the COVID situation is ended, policymakers may need to monitor the state of the financial industry closely to prevent the economy from a financial crisis.

5. CONCLUSIONS

Volatility spillovers are a reliable indicator of the transfer of risk between industries. The analysis of sectoral connectedness is particularly useful to analyze risk spillover mechanisms across industries during a crisis period. In this paper, we investigated the nature in which sectoral volatility returns of the Thai stock market have been interconnected over time. Using the daily data of 11 sectoral returns, we found that there have been several changes in connectedness during the pre-COVID and COVID periods. Looking through the connectedness index proposed by Diebold and Yilmaz (2014), the spillover effect has intensified during the COVID period. The Petrochemical and Chemical sector was the main transmitter while the Finance and Security sector was the main receiver during the COVID crisis. The COVID crisis could be different from a financial crisis. Laborda and Olmo (2021) studied the US stock market and found that the energy sector was the relevant risk transmitter during the COVID situation while the financial sector was the relevant risk transmitter during the global financial crisis. Our results are consistent with the findings of Laborda and Olmo (2021). The stock market's activity may serve as a leading predictor of what will happen in the real economy. The finding that the financial industry was the primary receiver of the volatility shocks raised concerns about the future stability of the financial system. The results obtained from the dynamic analysis utilizing the rolling-window estimations are in line with those of the comparative static analysis.

While this paper provides a good starting point for the study of the interconnectedness of sectoral volatilities, subsequent work could further build upon ours. For example, one might explore the merits of a more sophisticated model that is better at capturing the sectoral volatilities than our proposed GARCH (1,1) model. However, we leave these issues for further study.

ACKNOWLEDGEMENT: *The authors would like to thank Assistant Professor Dr.Wasin Siwasarit for his invaluable suggestions. Any mistake or error in this study is the authors' responsibility.*

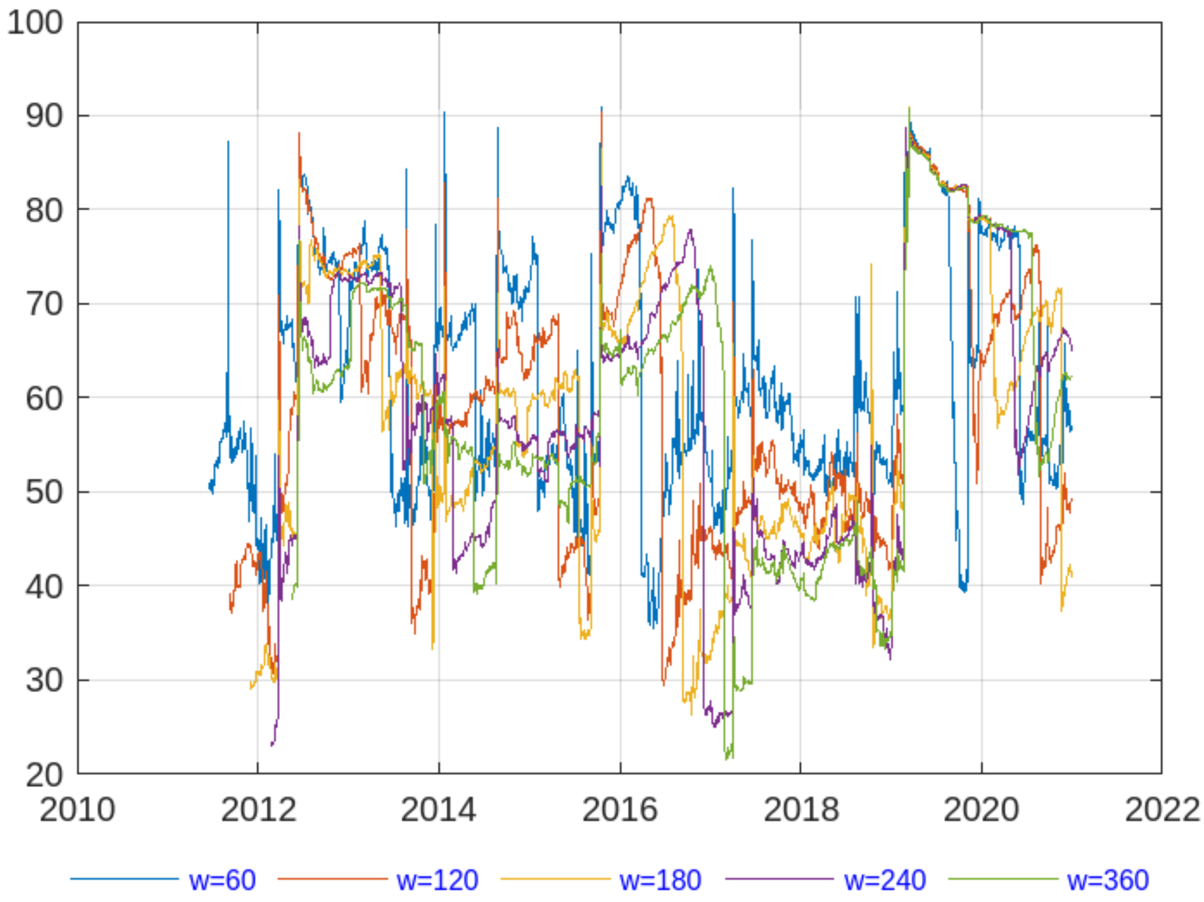
LITERATURE:

1. Ahmad, W., Hernandez, J.A., Saini, S. and Mishra, R.K., 2021. The US equity sectors, implied volatilities, and COVID-19: What does the spillover analysis reveal?. *Resources Policy*, *72*, p.102102.
2. Baek, S., Mohanty, S.K. and Glambosky, M., 2020. COVID-19 and stock market volatility: An industry level analysis. *Finance research letters*, *37*, p.101748.
3. Bui, H.Q., Tran, T., Pham, T.T., Nguyen, H.L.P. and Vo, D.H., 2022. Market volatility and spillover across 24 sectors in Vietnam. *Cogent Economics & Finance*, *10*(1), p.2122188.
4. Choi, S.Y., 2022. Dynamic volatility spillovers between industries in the US stock market: Evidence from the COVID-19 pandemic and Black Monday. *The North American Journal of Economics and Finance*, *59*, p.101614.
5. Costa, A., Matos, P. and da Silva, C., 2022. Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics. *Finance Research Letters*, *45*, p.102124.
6. Diebold, F.X. and Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), pp.158-171.
7. Diebold, F.X. and Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting*, *28*(1), pp.57-66.
8. Diebold, F.X. and Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), pp.119-134.
9. Diebold, F.X. and Yılmaz, K., 2015. *Financial and macroeconomic connectedness: A network approach to measurement and monitoring*. Oxford University Press, USA.
10. Ekinci, R. and Gençyürek, A.G., 2021. Dynamic Connectedness between Sector Indices: Evidence from Borsa Istanbul. *Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi, 16*(2), pp.512-534.
11. Hongsakulvasu, N., Khiewngamdee, C. and Liammukda, A., 2020. Does COVID-19 crisis affects the spillover of oil Market's return and risk on Thailand's sectoral stock return?: Evidence from bivariate DCC GARCH-in-mean model. *International Energy Journal*, *20*(4), pp.647-662.
12. Laborda, R. and Olmo, J., 2021. Volatility spillover between economic sectors in financial crisis prediction: Evidence spanning the great financial crisis and Covid-19 pandemic. *Research in International Business and Finance*, *57*, p.101402.
13. Panyagometh, K., 2020. The effects of pandemic event on the stock exchange of Thailand. *Economies, 8*(4), p.90.
14. Shahzad, S.J.H., Bouri, E., Kristoufek, L. and Saeed, T., 2021. Impact of the COVID-19 outbreak on the US equity sectors: Evidence from quantile return spillovers. *Financial Innovation*, *7*(1), pp.1-23.
15. Shen, Y.Y., Jiang, Z.Q., Ma, J.C., Wang, G.J. and Zhou, W.X., 2021. Sector connectedness in the Chinese stock markets. *Empirical Economics*, pp.1-28.
16. Suwannapak, S. and Chancharat, S., 2022. Stock Market Volatility Response to COVID-19: Evidence from Thailand. *Journal of Risk and Financial Management*, *15*(12), p.592.
17. Zhang, W., Zhuang, X., Wang, J., and Lu, Y., 2020. Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network. *The North American Journal of Economics and Finance*, *54*, p.101248.

APPENDIX.

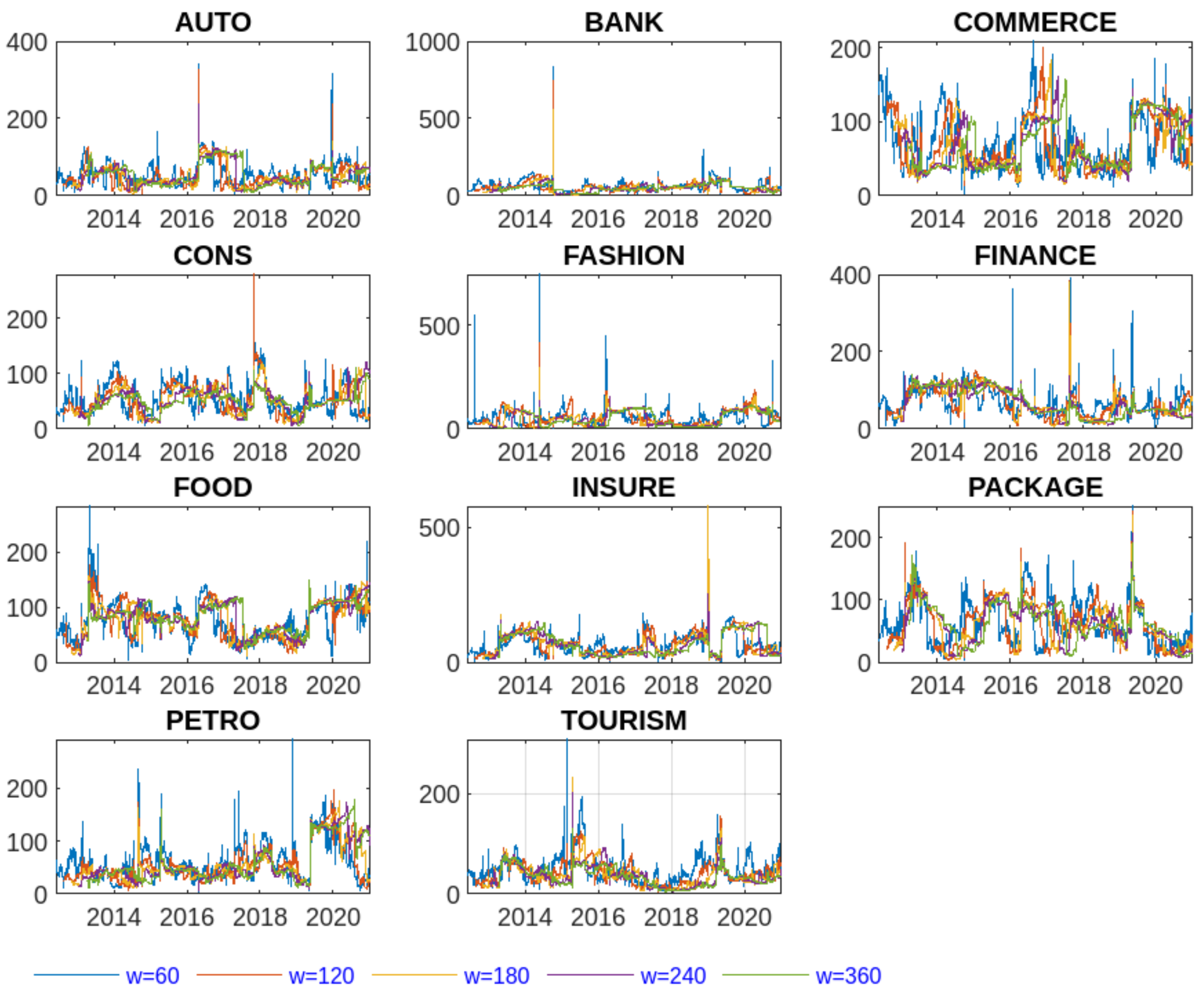
A1. Robustness test of TOTAL connectedness of the Stock Exchange of Thailand during 2012-2021

TOTAL DY index

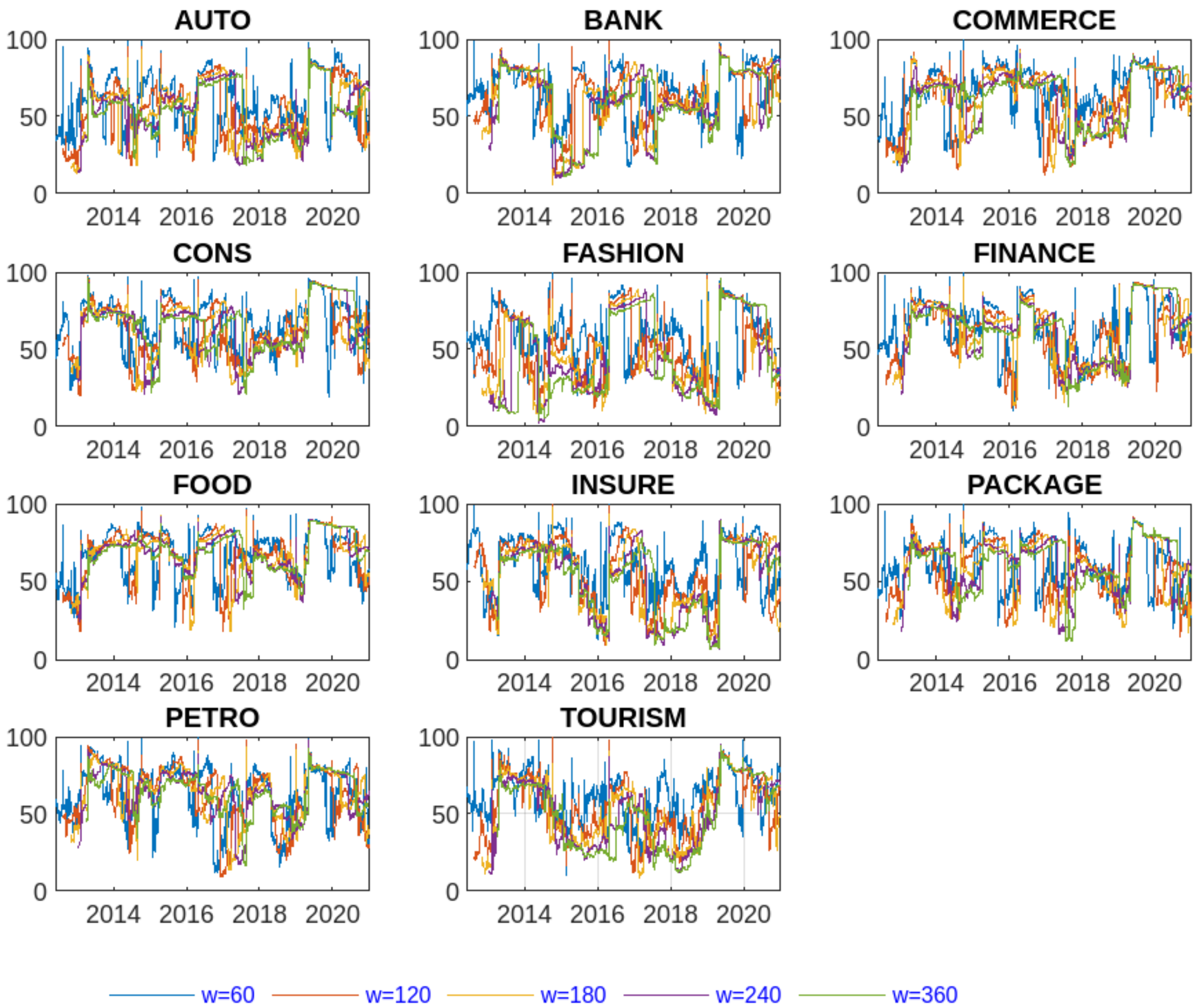


A2 Robustness test of sectoral connectedness of the Stock Exchange of Thailand during 2012-2021

A2.1. To-connectedness



A2.2. From-connectedness



A2.3. Net-connectedness (To-connectedness – From-connectedness)