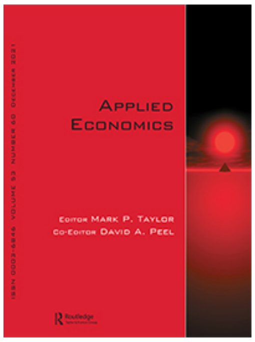

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Volatility Transmission Between the Japanese Stock Market and the Western Stock Market Indices: Time & Frequency Domain Connectedness Analysis with High-Frequency Data

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Volatility Transmission Between the Japanese Stock Market and the Western Stock Market Indices: Time & Frequency Domain Connectedness Analysis with High-Frequency Data

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ABSTRACT
Stock markets are the main source of financial fragility and the spillover effect due to the high level of connectedness. This study focuses on the connectedness between the Japanese stock market and the major Western stock market indices by performing time and frequency-domain connectedness analysis for the period between 4 January 2002, and 29 September 2020. The time-domain analysis shows that there is a high connectedness among stock market indices, and the net transmitter indices are SPX and AEX while net receiver indices are AORD and N225. The frequency-based analysis highlights that the connectedness between markets in the long term contains more information in contrast to short and medium terms. Similar to time-domain results, SPX is the net transmitter and N225 is the net receiver market indices in long term. Moreover, the dynamic analysis results illustrate the turbulent times of the volatility spillover in the long term with high and short-medium run with low spillover index. Dynamically, time-domain and long-term frequency-domain frameworks' findings give similar time variation illustrations.

KEYWORDS
Financial market; stock market; spillover effect; time-domain analysis; frequency-domain analysis

JEL CLASSIFICATION
G10; G15; C10; C53

I. Introduction

Major stock markets cover a large share of global market capitalization, connectedness between these markets is inevitable. The connectedness of stock markets has been the central of many studies. After the 1980s rapid increase in globalization dues to the financial liberalization, makes financial markets more connected to each other. The stock market is the most volatile market among other financial markets. On the other hand, the effect of any unexpected financial or non-financial issues can be seen firstly on stock markets in an economy than spread to the other markets. Financial Crises experiences in emerging market economies, 2008 Global Crisis, 2011 Eurozone Sovereign Debt Crisis and Coronavirus are such examples. So that, the connectedness analysis is the key concern for policymakers as well as financial economists, investors and portfolio managers.

Diebold and Yilmaz (2009) with their novel approach estimate financial market connectedness by naming the 'spillover index' with the decomposition of variance using a simple vector autoregression model. However, there is a possibility that variance decomposition may be dependent on the VAR order with the typical vector autoregression (VAR) method. To eliminate this possibility and to measure the spillover index without any dependence of variance decomposition according to an order of VAR model, the generalized VAR framework is developed by Diebold and Yilmaz (2012). Another generalized forecast error variance decomposition (GFEVD) based on the VAR framework, which provides a novel approach with the opportunity to examine the spillover index measurement based on the frequencies, by Barunik and Krehlik (2018). In the Asian context, Chow (2018) also applies Diebold and Yilmaz spillover index to investigate the volatility spillover among stock indexes of the United States, the United Kingdom and 10 ten Asian countries. They note that the degree of openness and financial crises influence spillover volatility. Moreover, Luo and Wang (2019) perform MHAR-DCC Model to test the high-frequency asymmetric volatility across stock markets. The results support the positive interaction between the volatility and the level of spillover

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Table 1. Representation of spillover table.

	x_1	x_2	x_N	From
x_1	$(\tilde{\Theta}_H)_{11}$	$(\tilde{\Theta}_H)_{12}$	$(\tilde{\Theta}_H)_{1N}$	$\sum_{l=1}^{N}(\tilde{\Theta}_H)_{1,l}, l\neq 1$
x_2	$(\tilde{\Theta}_H)_{21}$	$(\tilde{\Theta}_H)_{22}$	$(\tilde{\Theta}_H)_{2N}$	$\sum_{l=1}^{N}(\tilde{\Theta}_H)_{2,l}, l\neq 2$
x_N	$(\tilde{\Theta}_H)_{N1}$	$(\tilde{\Theta}_H)_{N2}$	$(\tilde{\Theta}_H)_{NN}$	$\sum_{l=1}^{N}(\tilde{\Theta}_H)_{N,l}, l\neq N$
To	$\sum_{k=1}^{N}(\tilde{\Theta}_H)_{k,1}, k\neq 1$	$\sum_{k=1}^{N}(\tilde{\Theta}_H)_{k,2}, k\neq 2$	$\sum_{k=1}^{N}(\tilde{\Theta}_H)_{k,N}, k\neq N$	$\frac{\sum_{k,l=1}^{N}(\tilde{\Theta}_H)_{k,l}}{\sum^{\tilde{\Theta}_H}}, k\neq l$

index. As one of the recent studies, Bagher and Ebrahimi (2020) examine the connectedness among different financial markets and commodity markets. Authors expand Diebold and Yilmaz (2012, 2014) methodology by performing the Hierarchical Vector Autoregression (HVAR). They point out that the Asian stock markets are the net receiver of shocks, while Western stock markets are the net transmitter of shocks mainly during the 2008 Global Crisis. Moreover, commodity and currency markets are highly connected to each other. Another study which constructed on Diebold and Yilmaz (2014) index is a study by Fernandez-Rodriguez and Sosvilla-Rivero (2020). They focus on the volatility transmission among stock markets and foreign exchange markets in seven advanced economies. The results of both static and dynamic analysis indicate that the volatility connectedness varies over time. There are also studies like those of Antonakakis and Kizys (2015), Maghyereh, Awartani, and Bouri (2016), Gabauer and Gupta (2018), and Yoon et al. (2019) which investigate the connectedness among different financial markets.

Thus, a large body of literature is conducted to explain the relationship between financial markets and the correlation between each other. However, limited number of studies that focus on the connectedness between Japan stock market and the major Western stock markets with high-frequency data. To the best of our knowledge, this study is the first one that focuses on this issue by applying frequency-domain connectedness analysis with high-frequency data for Japan stock market and Western stock markets and comparing with two aspects, time-domain and frequency-domain. Additionally, this study presents the level of connectedness in stock markets with new evidence, the spill over effect of the recent Coronavirus crash is higher than the global financial crisis in 2008.

The rest of this paper is organized as follows: after the introduction section, the following sections provide methodology and data while the empirical results are given in the fourth section. Finally, the last section concludes the analysis.

II. Methodology

This paper extensively investigates static and dynamic connectedness on the Japanese Stock Market and the Western Economies' stock markets. Our analysis employs time-domain connectedness introduced by Diebold and Yilmaz (2012) and the frequency-domain connectedness framework of Barunik and Krehlik (2018). Measurement of connectedness between stock markets requires the variance decomposition, based on the VAR model[1]

Table 1 shows the representation of the spillover table which introduced and later developed with 'directional spillover' by Diebold and Yilmaz (2009, 2012). Besides the time domain connectedness analysis, drawing attention to the characteristics of connectedness at different frequencies, Barunik & Krehlik's (2018) generalized forecast error variance decomposition method provides an examination of connectedness with spectral analysis in the short, medium and long periods.

III. Data

This study considers 12 different stock indices to examine the stock market connectedness covering the years between the years 2002 and 2020. The

[1]For detailed description of variance decomposition based on generalized VAR model see Appendix 1.

Table 2. Descriptive Statistics of Volatility Data.

	Represents	Min	Max	Median	Mean	Std. Dev.	Skewness	Kurtosis	ADF
AEX	Amsterdam Exchange	0.0021	0.0648	0.0074	0.0091	0.0059	2.8629	16.2533	−13.341*
AORD	All Ordinaries	0.0013	0.0691	0.0050	0.0061	0.0042	4.2897	38.9273	−17.032*
BFX	Belgium 20	0.0022	0.0607	0.0070	0.0083	0.0049	2.9831	19.2414	−14.058*
FCHI	CAC 40 (Paris)	0.0022	0.0716	0.0084	0.0100	0.0061	2.9025	18.1792	−13.708*
FTSE	London Stock Exchange	0.0012	0.1030	0.0074	0.0092	0.0063	3.9477	33.0045	−16.634*
GDAXI	DAX 30	0.0020	0.0767	0.0086	0.0106	0.0067	2.7319	15.1950	−13.356*
IBEX	Madrid Stock Exchange	0.0028	0.0742	0.0093	0.0105	0.0058	2.6150	17.2635	−15.750*
N225	Nikkei 225	0.0020	0.0620	0.0075	0.0086	0.0050	3.2378	21.6783	−18.272*
OSEAX	Oslo Stock Exchange	0.0026	0.1403	0.0079	0.0098	0.0066	4.7736	54.7795	−18.154*
SPX	Standard & Poor's 500	0.0011	0.0880	0.0066	0.0084	0.0065	3.4338	22.2191	−13.686*
SSMI	Swiss Market	0.0025	0.0745	0.0065	0.0080	0.0052	3.9929	30.3279	−14.582*
STOXX 50E	Euro Stoxx 50	0.0021	0.1041	0.0090	0.0108	0.0069	3.3164	23.9318	−15.168*

**Represents rejection with a 1% significance level the null hypothesis that a unit root. ADF unit root test lag is 1.*

indices included in the time and frequency domain connectedness analysis are as follows: stock market indices of Netherlands (AEX), Belgium (BFX), France (FCHI), Germany (GDAXI), Spain (IBEX), Switzerland (SSMI) and Eurozone (STOXX50E), representing the Western-European region; England (FTSE), S&P 500 index (SPX) for the USA; Australia's stock market index All Ordinaries (AORD), Norway's stock market index Oslo Stock Exchange All Share Index (OSEAX) and leading index Nikkei 225 (N225) for Japanese stock exchange. High-frequency data improves the predictive accuracy of the data and it is important in prediction for future volatility by presenting the market dynamics in volatility more deducible (Hansen and Lunde 2011). In this analysis, we use high-frequency data as computed using 5 min returns daily realized variance for stock market connectedness analysis which is obtained from Oxford-Man Institute Realized Library version 0.3 (Heber et al. 2009). The Oxford-Man Institute's realized variance estimation method follows Shephard and Sheppard (2010) description with background based on the studies of Andersen et al. (2010) and Barndorff-Nielsen and Shephard (2007). In this analysis, the realized data covering period is 4 January 2002 and 29 September 2020 with 4142 trading days and the missing observations are eliminated, public holidays of countries and first trade days of each year. Volatility data is calculated by taking the square root of the daily realized variance.

Table 2 lists descriptive statistics of realized volatility data with ticker symbols of countries' stock market indices. All indices show positive skewness and high kurtosis statistics. Variables have leptokurtic distribution with extremely high kurtosis values. OSEAX index kurtosis statistic is considerably higher than other indices. Therefore, they have non-normal distribution with positive skewness and high kurtosis values. ADF statistics of twelve variables indicate that all variables are stationary in their levels.

According to Figure 1, volatility data variables show moderate and strong positive relationships. While European country stock market indices have a high correlation coefficient with each other and with the United States, the stock market indices of Japan and Australia have relatively lower correlation coefficients with each other and with the stock market indices of other countries in the analysis. The strongest positive relationship is observed between AEX and FCHI indices with 0.96 correlation coefficient, while the second strongest interaction between FCHI and Euro STOXX50E indices with 0.95 correlation coefficient. The lowest positive relationship is between IBEX and N225 with 0.52 correlation coefficient. All variables' histogram is right-skewed; thus, the mean of variables is greater than their median with positive skewness statistic.

IV. Empirical Results

Time-domain connectedness analysis

Firstly, twelve stock market index volatility data is estimated with four order VAR which is determined according to Schwarz information criteria, following the approach described in section 2. In addition to the static time-domain

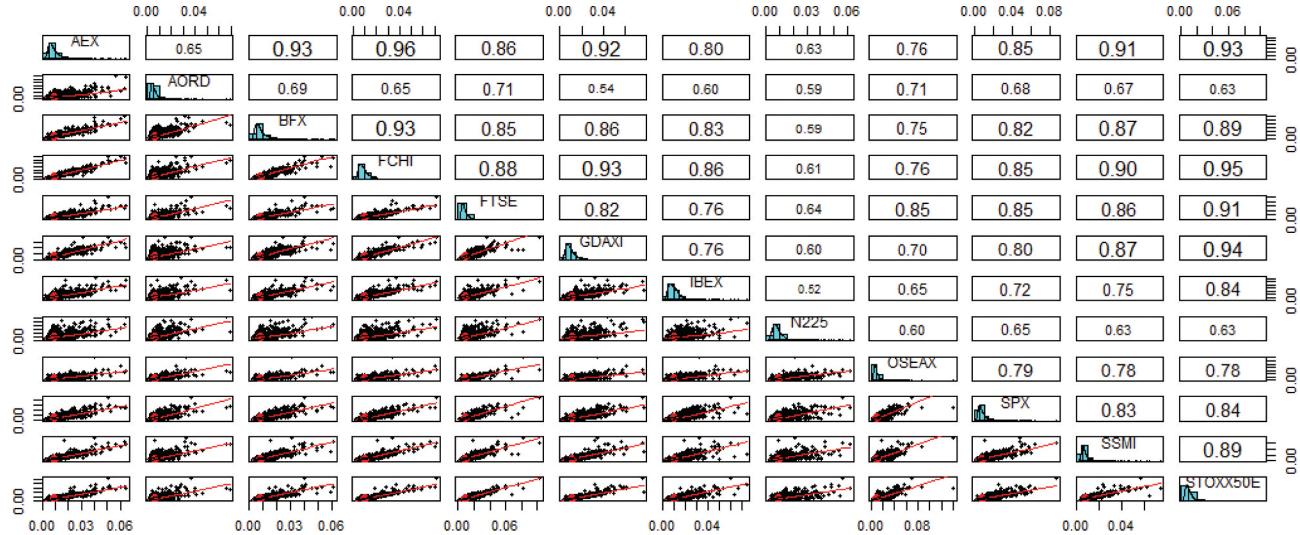

Figure 1. Histogram and Correlation. Scatter plot with a fitted line which shows the strength of the relationship, histogram with kernel density estimation and correlation coefficients.

Table 3. Time-Domain Analysis Spillover Table.

	AEX	AORD	BFX	FCHI	FTSE	GDAXI	IBEX	N225	OSEAX	SPX	SSMI	STOXX 50E	FROM
AEX	15.55	1.57	11.10	12.00	6.84	10.39	8.18	1.11	4.93	8.90	10.03	9.40	7.04
AORD	7.36	22.54	7.25	6.35	8.58	4.07	5.24	3.48	9.76	10.58	8.64	6.15	6.45
BFX	**12.86**	2.17	15.45	11.35	7.12	9.12	8.93	1.10	5.13	8.52	9.35	8.90	7.05
FCHI	**13.15**	1.60	10.56	13.37	7.13	10.62	9.34	1.04	4.86	8.91	9.32	10.10	7.22
FTSE	10.31	2.55	8.64	9.54	14.09	8.29	6.82	1.72	8.06	10.34	9.06	10.57	7.16
GDAXI	**13.08**	0.87	9.86	**12.13**	6.70	15.60	7.99	1.18	3.96	8.33	9.45	10.84	7.03
IBEX	11.12	1.68	10.50	11.70	6.58	8.88	17.77	1.16	4.58	7.81	8.01	10.22	6.85
N225	6.94	4.18	4.61	5.69	7.20	5.53	4.75	29.26	6.59	10.69	7.03	7.54	5.89
OSEAX	8.67	3.70	7.09	7.65	10.34	6.11	5.32	1.57	20.80	11.53	8.68	8.55	6.60
SPX	10.23	2.17	7.77	9.47	8.33	8.01	6.38	1.72	7.08	21.74	8.70	8.38	6.52
SSMI	**12.10**	1.94	9.19	10.31	7.76	9.47	6.89	1.41	5.87	9.47	16.62	8.96	6.95
STOXX 50E	11.96	1.46	9.58	11.56	8.38	11.14	9.08	1.35	5.39	8.60	8.97	12.52	7.29
TO	9.81	1.99	8.01	8.98	7.08	7.64	6.58	1.40	5.52	8.64	8.10	8.30	***82.06***

Table 4. Time-Domain Connectedness Net Spillovers.

	To	From	Net		To	From	Net
AEX	9.8134	7.0373	**2.7762**	*IBEX*	6.5758	6.8526	−0.2768
AORD	1.9913	6.4548	**−4.4635**	*N225*	1.4037	5.8949	**−4.4912**
BFX	8.0135	7.0462	0.9673	*OSEAX*	5.5194	6.6004	−1.0810
FCHI	8.9802	7.2189	1.7614	*SPX*	8.6396	6.5217	**2.1180**
FTSE	7.0794	7.1591	−0.0797	*SSMI*	8.1042	6.9483	1.1559
GDAXI	7.6359	7.0329	0.6030	*STOXX50E*	8.3007	7.2902	1.0105

analysis results, also connectedness analysis is examined dynamically based on the rolling window approach.[2]

The overall spillover index is 82.06%.

Table 3 shows the static analysis of the variables estimated generalized variance decomposition according to the forecast horizon for 10 days. The total spillover index of stock indices are 82% which indicate that 82.06% of the forecast error variance due to this spillover effect across indices. The bold numbers in Table 3 show the highest five spillovers among the stock indices in the time domain analysis, excluding the contribution of stock indices to each other. Four of these are the volatility spillover from AEX stock index to other stocks, respectively, to FCHI at 13.15%, to GDAXI at 13.08%, to BFX at 12.86% and to SSMI at 12.10%. Consequently, the highest directional

[2]Robustness check for rolling window according to lag and forecast horizons see Appendix 2.

spillover to others which is also a composite of the total spillover index and demonstrating 9.81% of the forecast error variance is explained by AEX. When its contribution to AEX from other market indices is also subtracted, AEX is the highest net transmitter (2.77%) among all indices (see Table 4). SPX follows AEX as a second-most transmitter among indices.

The N225, as the index of the Tokyo Stock Market, contributes the most to itself with 29.26% in all indices and the least to other markets. Naturally, the N225 is the net receiver from other indices with the lowest net spillover. The highest contribution to this receiving position of N225 coming shock from SPX with 16.69%. The second net receiver index is AORD, similarly also AORD most volatility transmission shock coming from SPX with 10.58%. According to static time-domain connectedness results, N225 most responded to shocks with 10.69% from SPX, 7.54% from STOXX50E and 7.20% from FTSE. Consequently, AEX & SPX are the most net transmitter stock indices to other markets while AORD and N225 are the most net receivers from other markets with relatively smaller shock transmissions to other markets as reported in Table 4.

Table 5. Net Pairwise Spillovers of N225 Index.

N225 ←			
AEX	5.83	*IBEX*	3.59
AORD	**0.70**	*OSEAX*	5.02
BFX	3.51	*SPX*	**8.97**
FCHI	4.65	*SSMI*	5.62
FTSE	5.48	*STOXX50E*	6.19
GDAXI	4.35		

Table 5 lists net pairwise spillovers of N225 as a difference between transmitted shocks from Western stock market indices to N225 and transmitted shocks to Western stock market indices from N225. In net terms, the highest volatility spillover from SPX to N225 is 8.97% and the lowest volatility spillover from AORD to N225 is 0.70%. In light of the evidence, N225 is a net shock receiver from all western stock market indices.

Static analysis results show the average spillover index, while the variations of the index with respect to time can be achieved by dynamic analysis. Therefore, rolling window estimation gives information on spillover index day by day. To dynamically examine the spillover index for the years between 2002 and 2020, it is estimated with 200 rolling windows and a 10-day forecast horizon, again with generalized forecast error variance decomposition framework. Similarly, the VAR order is chosen as 4 according to the Schwarz information criteria.

Figure 2 demonstrates the total spillover index variations between the years 2002 and 2020, and the highest spillover indexes are seen in the years 2008–2009, 2011, 2015, 2016 and 2020.

As can be seen in Table 6 the stock markets have faced several major financial events which led to an increase in the spillover effects due to the connectedness among the markets. The connectedness

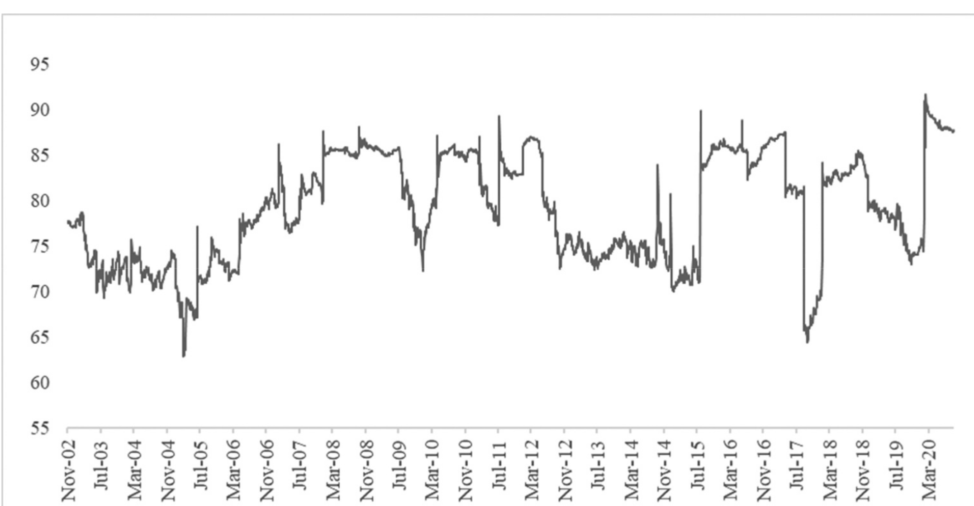

Figure 2. Dynamic Time-Domain Total Volatility Spillovers.

Table 6. Major Events which affect the spillover index (2008–2020).

Date	Spillover Index	Event
10/10/2008	88.06%	Lehman-Brothers Collapse
09/08/2011	89.27%	Lowering the U.S. credit rating & debt crisis in Europe
24/08/2015	89.78%	Chinese stock market turbulence
24/06/2016	88.72%	Brexit vote
09/03/2020	91.61%	Coronavirus crash

between stock indices exceeded 90% in the period covered by the analysis at the end of February 2020 and the beginning of March 2020, and the highest spillover index is 91.61% on 9 March 2020, while the fifth highest index is 88.06% on 10 October 2008.

Figure 3 illustrates the dynamic net spillover index of stock market indices. Generally, the U.S. stock market index SPX and European stock indices, AEX, BFX, FCHI, GDAXI, SSMI and Stoxx50 are net transmitters. Thus, their shocks affect other stock market indices among the sample. S&P's 500 index's net spillover is the highest spillover index with almost 17% in February 2018. SSMI net spillover is 16.76% on 15 January 2015, which is the second-highest observed net spillover among market indices in this dynamic analysis.

On 15 January 2015, net spillover of the Swiss Market Index is the second highest observed net spillover among market indices with 16.76%. At that time, the Swiss Central Bank intervenes that the Swiss Franc drop the cap against the Euro, is led to observe one of lowest net spillover index of N225 with −4.14% according to the previous day.

Figure 4 shows dynamically to, from and net spillovers of the N225 in the sample period. Dynamically, the interconnectedness of N225 with other stock indices reaction is similar to the reaction of other indices against global events. But the net receiver position of N225 is mostly affected by a major earthquake in 2011 which led to change its position. N225 index is a net receiver with negative net spillover except for three periods. N225 is

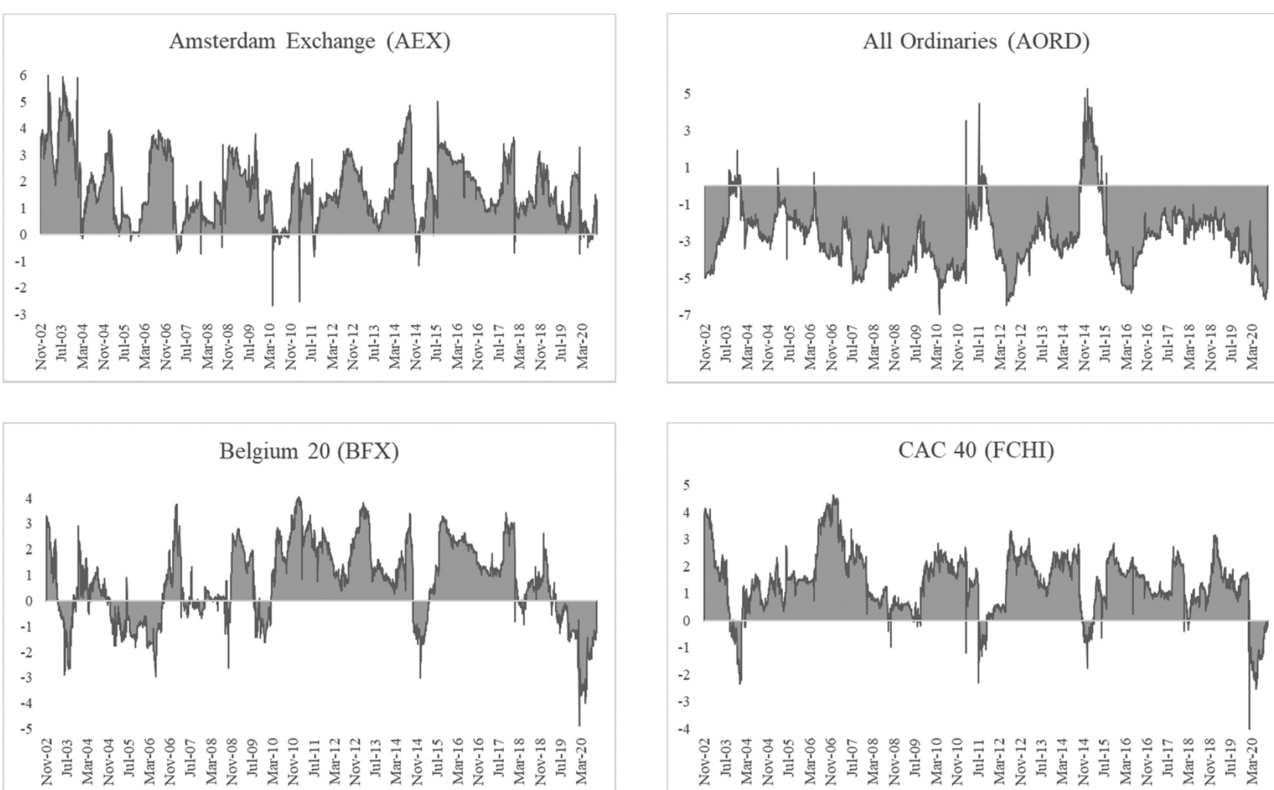

Figure 3. Dynamic Time-Domain Connectedness Analysis Net Spillovers of Stock Indices.

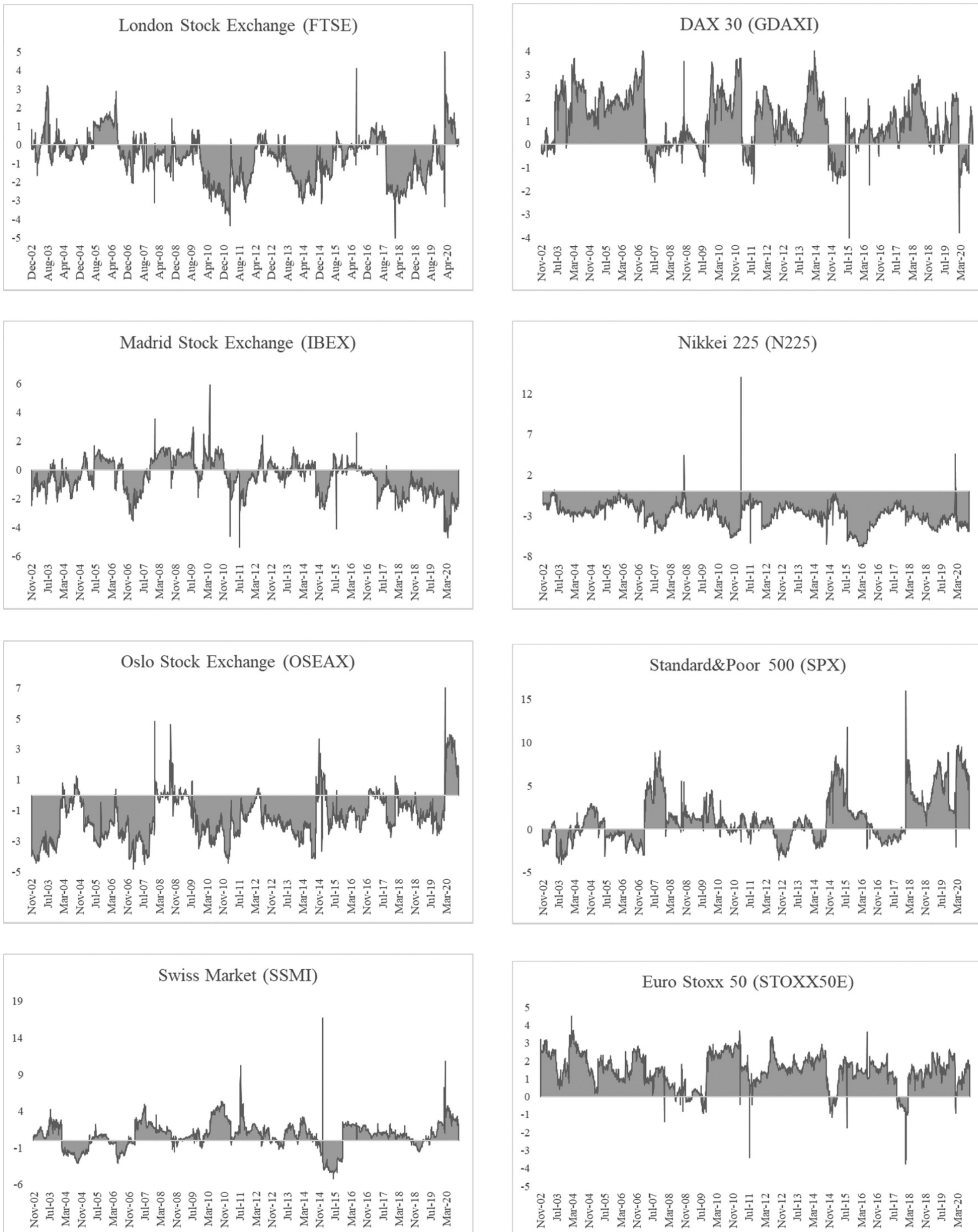

Figure 3. Continued

a transmitter with 4.40% net spillover index on 28 October 2008, 13.99% net spillover index on 15 March 2011 and a 4.61% net spillover index on 3 March 2020.

Frequency-Domain analysis

In our frequency domain generalized VAR model estimation, we use the Lasso (*Least absolute shrinkage and selection operator*) penalty for

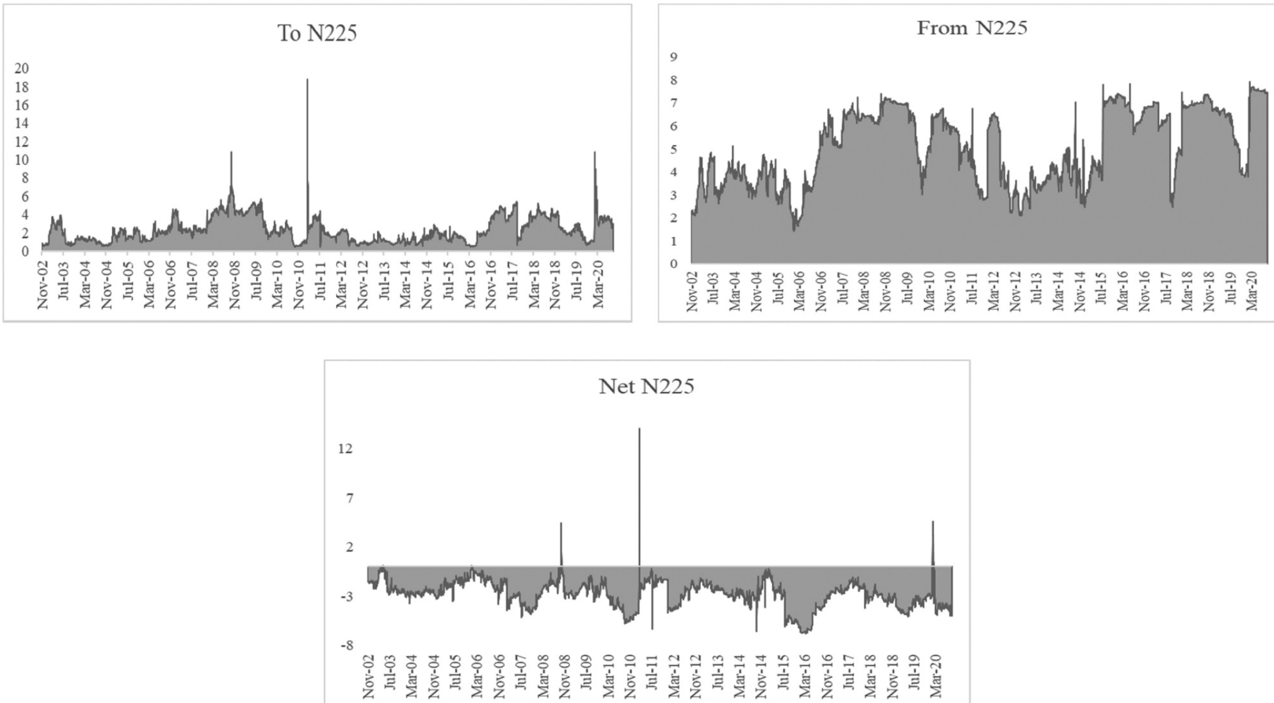

Figure 4. N225 Dynamic To, From, Net Spillover.

analysis of realized volatility data with logarithmic form. Lasso technique developed by Tibshirani (1996), minimized the forecast errors, and equals the zero some coefficients, and shrinking the other coefficients, thus gives more accuracy to the estimation results. Following the method described in section 2, stock indices are estimated[3] using Lasso penalty with generalized VAR framework, and Table 7 shows spillover index values as 1–5 days (short term), 5–21 days (medium term), and after 21 days (long term) as a result of spectral representation of variance decomposition. Dynamic frequency domain connectedness analysis is conducted with 150 rolling windows and 100-day forecast horizon.

Frequency decomposition connectedness of stock indices, as reported in Table 7, shows low spillover indexes in short (9%) and medium terms (8.75%) but fairly high in the long term (64.90%). Firstly, SPX is the biggest contributor index for shock transmission in long term. Respectively, the highest directional shocks come from SPX to OSEAX (10.66%), to N225 (10.58%), to FTSE index (9.52%) and to SSMI (9.19%). Next, one of the highest directional spillover is observed in FCHI index to the IBEX index (9.15%). In the frequency-based connectedness framework, it is observed that the N225 receives the most shocks from the SSMI (7.24%) after SPX, in the long term. Hence, N225 shock transmission among European stock markets comes highest from SSMI in the long term. This finding supports the evidence that the net shock receiver position of N225 as a result of the intervention of the Swiss Central Bank on 15 January 2015 is obtained in the time-domain analysis framework.

Table 8 shows AEX and FCHI stock indices are the biggest net transmitter to other stock indices, both in the short term and mid-term. However, the SPX index is the biggest net transmitter and N225 is the biggest net receiver stock market index, in the long term. The long-term result is nearly parallel to the static time-domain connectedness analysis findings.

Figure 7 shows dynamic frequency-based connectedness analysis spillover index between 2002 and 2020, estimation with 150 days rolling window and 100 days forecast horizon. In the short term,

[3]Estimation is conducted with frequency Connectedness (Krehlik, 2020) and BigVar (Nicholson et al., 2019) packages under R Program.

Table 7. Frequency-Domain Analysis Spillover Table.

a) One to five day

	AEX	AORD	BFX	FCHI	FTSE	GDAXI	IBEX	N225	OSE AX	SPX	SSMI	STOX X50E	FROM ABS	FROM WTH
AEX	2.52	0.07	1.49	1.95	0.70	1.47	1.26	0.10	0.33	0.57	1.24	1.50	0.89	6.71
AORD	0.29	8.83	0.30	0.31	0.58	0.25	0.26	0.41	0.59	0.41	0.30	0.41	0.34	2.58
BFX	1.69	0.10	2.90	1.74	0.70	1.34	1.29	0.09	0.34	0.49	1.11	1.36	0.85	6.44
FCHI	2.03	0.08	1.60	2.64	0.79	1.64	1.47	0.10	0.36	0.59	1.25	1.80	0.98	7.36
FTSE	1.03	0.26	0.91	1.12	4.10	1.05	0.69	0.17	1.10	0.73	0.90	1.84	0.82	6.16
GDAXI	1.64	0.06	1.31	1.76	0.79	2.82	1.22	0.10	0.35	0.56	1.27	1.86	0.91	6.88
IBEX	1.56	0.08	1.43	1.78	0.59	1.37	3.14	0.08	0.28	0.48	1.09	1.53	0.86	6.45
N225	0.29	0.39	0.23	0.28	0.34	0.26	0.19	7.93	0.23	0.31	0.33	0.38	0.27	2.03
OSEAX	0.76	0.44	0.69	0.78	1.61	0.72	0.52	0.18	6.28	0.58	0.65	1.26	0.68	5.16
SPX	0.98	0.07	0.74	0.98	0.82	0.87	0.66	0.14	0.40	4.18	0.75	0.93	0.61	4.61
SSMI	1.38	0.10	1.08	1.34	0.67	1.26	0.96	0.12	0.32	0.48	2.80	1.14	0.74	5.56
STOXX50E	1.72	0.14	1.37	1.98	1.45	1.91	1.40	0.16	0.66	0.63	1.18	2.97	1.05	7.92
TOABS	1.12	0.15	0.93	1.17	0.75	1.01	0.83	0.14	0.41	0.49	0.84	1.17	**9.00**	
TOWTH	8.41	1.13	7.01	8.80	5.68	7.62	6.24	1.04	3.12	3.68	6.33	8.81		67.86

b) Five to twenty-one day

	AEX	AORD	BFX	FCHI	FTSE	GDAXI	IBEX	N225	OSE AX	SPX	SSMI	STOX X50E	FROM ABS	FROM WTH
AEX	1.88	0.07	1.26	1.57	0.66	1.31	1.04	0.10	0.32	0.83	1.15	1.28	0.80	6.95
AORD	0.58	4.50	0.56	0.61	0.86	0.47	0.51	0.34	0.70	0.81	0.56	0.72	0.56	4.88
BFX	1.40	0.11	2.07	1.43	0.64	1.12	1.11	0.09	0.32	0.75	1.00	1.16	0.76	6.61
FCHI	1.56	0.09	1.27	1.79	0.69	1.36	1.22	0.10	0.32	0.81	1.07	1.39	0.82	7.16
FTSE	1.13	0.24	1.05	1.14	1.82	1.01	0.79	0.15	0.61	1.08	1.02	1.32	0.79	6.90
GDAXI	1.50	0.06	1.14	1.52	0.70	2.14	1.04	0.09	0.31	0.75	1.09	1.52	0.81	7.05
IBEX	1.31	0.10	1.18	1.48	0.54	1.15	2.50	0.08	0.26	0.59	0.91	1.29	0.74	6.45
N225	0.56	0.32	0.43	0.54	0.51	0.50	0.37	5.86	0.30	0.92	0.61	0.62	0.47	4.12
OSEAX	0.93	0.36	0.75	0.90	1.24	0.80	0.58	0.17	3.15	1.24	0.77	1.14	0.74	6.44
SPX	1.06	0.10	0.79	1.03	0.82	0.93	0.71	0.17	0.46	3.24	0.89	0.98	0.66	5.75
SSMI	1.28	0.10	1.01	1.23	0.67	1.13	0.87	0.13	0.32	0.79	2.18	1.06	0.72	6.22
STOXX50E	1.51	0.08	1.19	1.60	0.89	1.58	1.25	0.11	0.40	0.85	1.05	1.80	0.88	7.61
TOABS	1.07	0.14	0.89	1.09	0.68	0.95	0.79	0.13	0.36	0.78	0.84	1.04	**8.75**	
TOWTH	9.28	1.19	7.71	9.46	5.95	8.23	6.87	1.11	3.13	6.82	7.33	9.05		76.13

c) Longer than twenty-one-day

	AEX	AORD	BFX	FCHI	FTSE	GDAXI	IBEX	N225	OSE AX	SPX	SSMI	STOX X50E	FROM ABS	FROM WTH
AEX	9.82	0.90	7.42	9.03	5.10	8.21	6.27	1.02	2.86	8.66	7.97	8.08	5.46	7.26
AORD	6.52	11.72	5.79	6.56	6.25	5.26	5.50	1.56	4.66	8.95	6.33	6.72	5.34	7.10
BFX	8.89	1.18	9.37	8.90	5.09	7.52	7.06	1.00	2.91	8.35	7.53	7.86	5.52	1.34
FCHI	8.94	1.01	7.29	9.26	4.96	8.02	7.12	0.96	2.76	8.09	7.39	8.16	5.39	1.17
FTSE	8.12	1.67	7.00	8.02	7.04	7.11	5.86	1.18	3.61	**9.52**	7.66	7.97	5.64	7.50
GDAXI	9.04	0.72	6.98	8.86	5.00	9.99	6.13	0.93	2.69	8.01	7.49	8.52	5.36	7.13
IBEX	8.55	1.19	7.39	**9.15**	4.46	7.44	12.05	0.84	2.49	6.65	6.72	8.25	5.26	6.99
N225	7.05	1.59	5.46	6.80	5.18	6.25	4.70	12.53	3.11	**10.58**	**7.24**	6.80	5.40	7.17
OSEAX	7.34	1.92	5.81	7.01	6.52	6.42	4.36	1.29	7.94	**10.66**	6.86	7.35	5.46	7.26
SPX	8.22	1.11	6.37	7.95	5.81	7.27	5.48	1.38	3.60	14.95	7.64	7.55	5.20	6.91
SSMI	8.94	1.10	7.15	8.63	5.45	7.87	6.13	1.26	3.06	**9.19**	10.96	7.85	5.55	7.38
STOXX50E	8.58	0.86	6.82	8.63	5.08	8.24	6.82	0.94	2.77	7.84	7.02	8.52	5.30	7.04
TOABS	7.52	1.11	6.12	7.46	4.91	6.64	5.45	1.03	2.88	8.04	6.65	7.09	**64.90**	
TOWTH	9.99	1.47	8.14	9.91	6.52	8.82	7.24	1.37	3.82	10.69	8.84	9.43		86.25

graph trend is like a cycle with fluctuations and the total spillover index exceeds 40% with certain cycles. Before sudden decrease, short term fluctuations accumulate impact on the long-term effect. For example, in 2008 and 2020, in short and mid-terms, the spillover index closest to zero, but we can see the uncertainty impact in the long-term with the highest spillover index. The effects of unexpected financial and non-financial events appear in the long term as a high connectedness between markets on specific event dates.

In addition to the time domain dynamic results of N225, Figure 8 shows in the long period there is mutual shock transmission between Nikkei 225 and other stock market indices at beginning of 2020, and net spillover is remarkably close the

Table 8. Frequency Domain Connectedness Net Spillovers.

1–5 Days				5–21 Days				21-Days			
	To	From	Net		To	From	Net		To	From	Net
AEX	1.11517	0.89015	**0.22502**	*AEX*	1.06715	0.79870	**0.26845**	*AEX*	7.51507	5.46001	**2.05506**
AORD	0.14942	0.34188	−0.19246	*AORD*	0.13675	0.56084	−0.42408	*AORD*	1.10562	5.34317	−4.23754
BFX	0.92952	0.85344	0.07609	*BFX*	0.88623	0.76020	0.12603	*BFX*	6.12315	5.52480	0.59836
FCHI	1.16730	0.97588	**0.19142**	*FCHI*	1.08762	0.82367	**0.26395**	*FCHI*	7.46017	5.39245	**2.06772**
FTSE	0.75289	0.81644	−0.06356	*FTSE*	0.68469	0.79348	−0.10879	*FTSE*	4.90855	5.64298	−0.73442
GDAXI	1.01004	0.91177	0.09828	*GDAXI*	0.94628	0.81086	0.13542	*GDAXI*	6.63521	5.36452	1.27069
IBEX	0.82700	0.85567	−0.02866	*IBEX*	0.79049	0.74127	0.04922	*IBEX*	5.45124	5.26193	0.18931
N225	0.13834	0.26977	−0.13143	*N225*	0.12810	0.47359	−0.34550	*N225*	1.03046	5.39624	**−4.36579**
OSEAX	0.41320	0.68347	−0.27027	*OSEAX*	0.36036	0.74061	−0.38025	*OSEAX*	2.87780	5.46198	−2.58417
SPX	0.48747	0.61131	−0.12384	*SPX*	0.78404	0.66067	0.12337	*SPX*	8.04215	5.19707	**2.84508**
SSMI	0.83912	0.73749	0.10162	*SSMI*	0.84292	0.71542	0.12750	*SSMI*	6.65374	5.55276	1.10099
STOXX 50E	1.16759	1.04980	**0.11780**	*STOXX 50E*	1.04032	0.87563	**0.16468**	*STOXX 50E*	7.09454	5.29982	1.79472

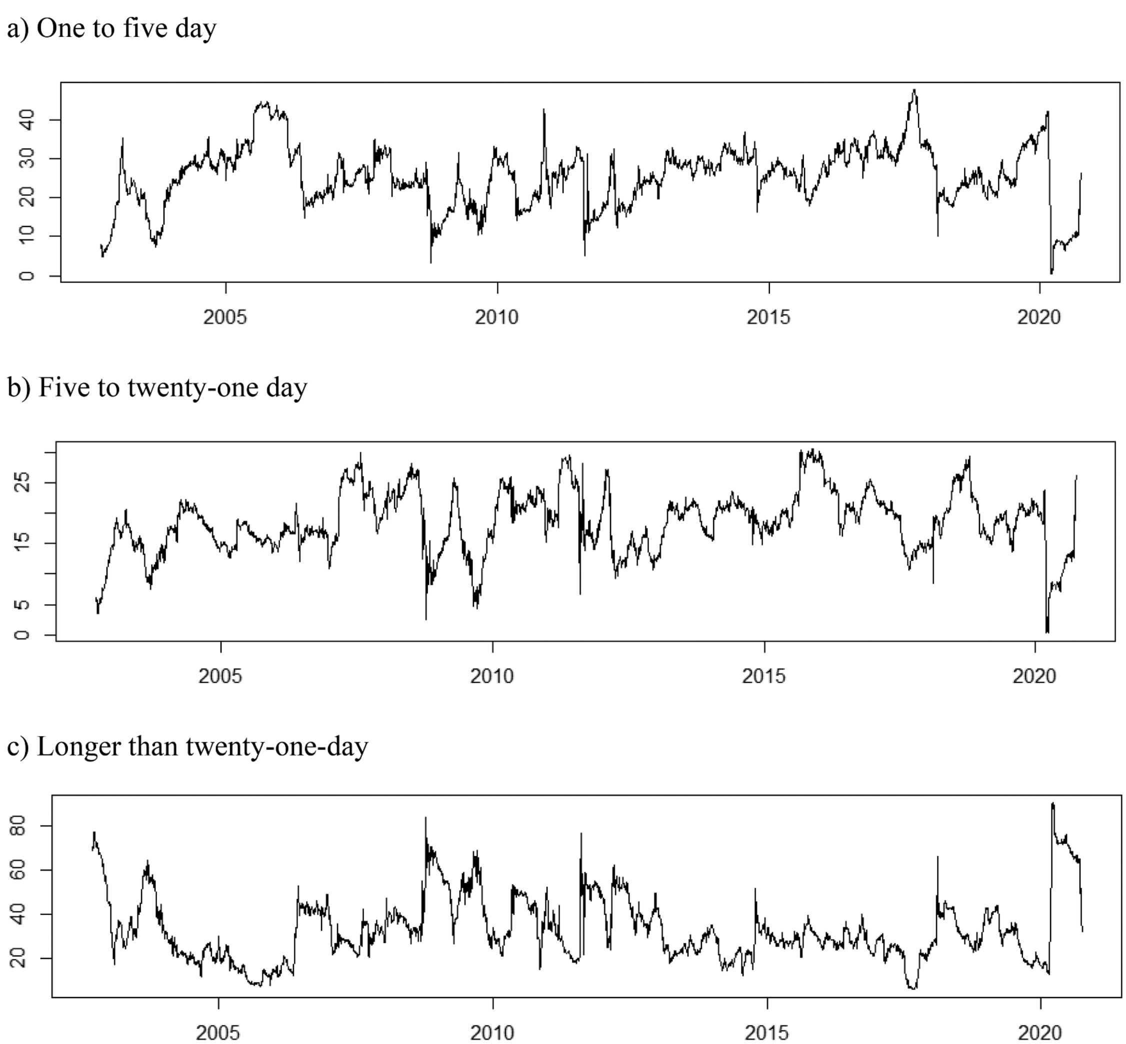

Figure 7. Dynamic Frequency-Domain Total Volatility Spillovers.

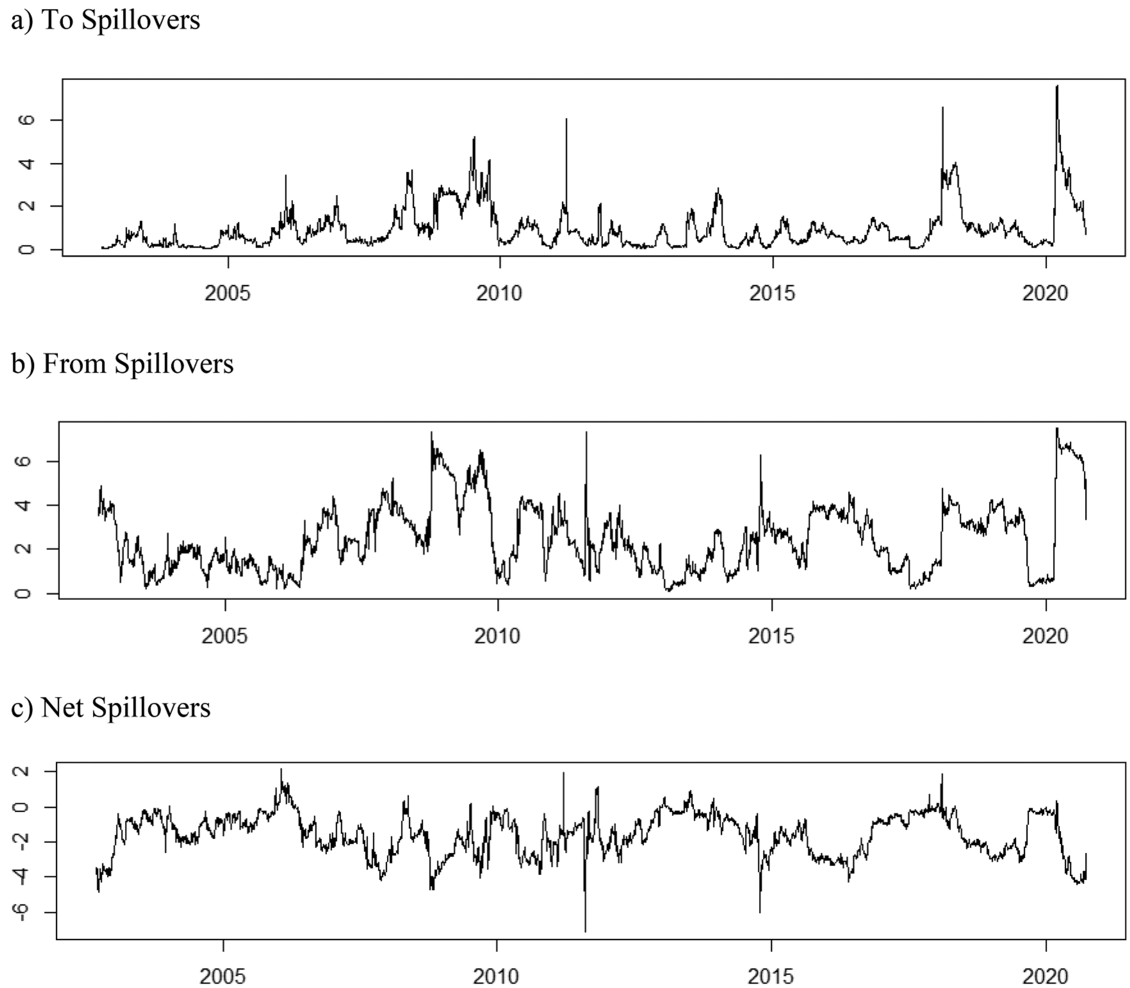

Figure 8. Dynamic Frequency-Domain of N225 To, From, and Net Spillover in Long Term.

zero. Similarly, N225 is a net shock receiver for long period, and in 2008, 2011, 2014 and 2020 highly affectable shocks are observed from N225 towards Western stock market indices. While the events with global impacts caused mutual shock transfer between N225 and other stock indices, the earthquake occurred in Japan which causes shock transmission to other markets from N225 in 2011. The European debt crisis, changes of US credit rating in 2011, and Swiss Central bank's intervention in 2015 that caused the shock receiver index position of N225 without shock transmission from N225 to other markets.

Frequency-domain connectedness analysis demonstrates low spillover effects in the stock markets of all countries in the short term and medium term. The analysis that reflects the long-term results includes more information for the spillover effect between stock market indices. However, in the long term, the shocks that occurred in the SPX indexes as the net transmitter affecting the stock markets of other countries. Most shock transmission occurs from the net transmitter index to OSEAX and the Japanese stock index (N225).

V. Conclusion

The connectedness of the stock markets of Japan and eleven Western stock market indexes are examined with high-frequency data in time-domain and frequency-domain connectedness frameworks. In the analysis performed with a large sample range and high-frequency data, taken into account the high dimension in VAR, and we use Lasso penalty for frequency-domain analysis. Thus, in addition to examining the short-, medium- and long-term effects of connectedness analysis, we discuss more accurate results with Lasso penalty give zero coefficients in the VAR system.

The results from both frameworks indicate that connectedness among the stock market indices reaches the highest spillover index during Covid-19. Time-domain analysis indicates that after the highest connectedness index among stock market indices resulting from the collapse of Lehman-Brothers, there are four periods of high connectedness index. These are according to the ascent order of connectedness index, respectively, the Brexit vote in 2016, the US's credit rating down and the European Debt Crisis in 2011, the Chinese stock market turbulence in 2015, and the market crash due to Coronavirus pandemic in March 2020. All these results show that unexpected sudden events increase the connectedness between stock markets and similar results are obtained with the increasing connectedness in the crisis periods in the literature. AEX and SPX are the most net transmitter stock indices to other markets while AORD and N225 are the most net receivers from other markets with relatively smaller shock transmissions to other markets. Moreover, the stock markets have faced several financial and non-financial issues such as the 2008 collapse of Lehman Brothers, the 2011 Eurozone Sovereign debt crisis, the pandemic which led to the highest spillover index values. At the time of some of these events, the shocks of the N225 have a more spillover effect to Western indices than other shocks that come to N225. In both frames, the analysis results show the N225's shock transmissions from the SPX at the most among stock markets indices, while the static frequency-based frame result indicates that the highest shock transmission comes from the SSMI to the N225 after the SPX in the long-term.

Our analysis acknowledges Japan stock market stands to the shocks from Western countries with a net receiver position. Therefore, Western stock markets shocks impact on the Japanese stock market index highly. The findings of this study can potentially be used for forecasting the behaviour of stock markets. Especially, despite the N225's stable shock receiver position, major events related to the Japanese stock market such as the earthquake that occurred in 2011 cause highly shock transmission from Nikkei 225 to Western stock markets.

The results indicate that all of these issues mentioned above to be empirically valid to explain the level of connectedness. Thus, the nature of the connectedness among stock market indices likely to be dependent on the characteristics of the particular stock market as well as the global financial and non-financial issues.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Andersen, T. G., T. Bollerslev, and F. X. Diebold. 2010. "Parametric and Nonparametric Volatility Measurement." In *Handbook of Financial Econometrics: Tools and Techniques*, edited by Y. Ait-Sahalia and L. P. Hensen, 67–137. North-Holland: Amsterdam. doi:10.1016/B978-0-444-50897-3.50005-5.

Antonakakis, N., and R. Kizys. 2015. "Dynamic Spillovers between Commodity and Currency Markets." *International Review of Financial Analysis* 41: 303–319. doi:10.1016/j.irfa.2015.01.016.

Bagher, E., and S. B. Ebrahimi. 2020. "Estimating Network Connectedness of Financial Markets and Commodities." *Journal of System Engineering Society of China* 29 (5): 572–589. doi:10.1007/s11518-020-5465-1.

Barndorff-Nielsen, O. E., and N. Shephard. 2007. "Variation, Jumps, Market Frictions and High Frequency Data in Financial Econometrics." In *Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress*, edited by R. Blundell, T. Persson, and W. K. Newey, 328–372. Vol. III. Cambridge, UK: Cambridge University Press.

Barunik, J., and T. Krehlik. 2018. "Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk." *Journal of Financial Econometrics* 16 (2): 271–296. doi:10.1093/jjfinec/nby001.

Chow, H. K. 2018. "Volatility Spillover and Linkages in Asian Stock Markets." *Emerging Markets Finance and Trade* 53: 2770–2781. doi:10.1080/1540496X.2017.1314960.

Diebold, F. X., and K. Yilmaz. 2009. "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets." *The Economic Journal* 119 (534): 158–171. doi:10.1111/j.1468-0297.2008.02208.x.

Diebold, F. X., and K. Yilmaz. 2012. "Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers." *International Journal of Forecasting* 28 (1): 57–66. doi:10.1016/j.ijforecast.2011.02.006.

Diebold, F. X., and K. Yilmaz. 2014. "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms." *Journal of Econometrics* 182 (1): 119–134. doi:10.1016/j.jeconom.2014.04.012.

Fernandez-Rodriguez, F., and S. Sosvilla-Rivero. 2020. "Volatility Transmission between Stock and Foreign Exchange Markets: A Connectedness Analysis." *Applied Economics* 52 (19): 2096–2108. doi:10.1080/00036846.2019.1683143.

Gabauer, D., and R. Gupta. 2018. "On the Transmission Mechanism of Country-specific and International Economic Uncertainty Spillovers: Evidence from a TVP-VAR Connectedness Decomposition Approach." *Economics Letters* 171: 63–71. doi:10.1016/j.econlet.2018.07.007.

Hansen, P. R., and A. Lunde. 2011. "Forecasting Volatility Using High-frequency Data." In *The Oxford Handbook of Economic Forecasting*, edited by M. P. Clements and D. F. Hendry (pp. 525-556). New York: Oxford University Press. doi:10.1093/oxfordhb/9780195398649.013.0020.

Heber, G., A. Lunde, N. Shephard, and K. Sheppard (2009). Oxford-Man Institute's Realized Library, Version 0.3 [Dataset]. Oxford-Man Institute: University of Oxford. Access Date: 12 10 2020.http://10.898

Krehlik, T. (2020). Frequency Connectedness: Spectral Decomposition of Connectedness Measures. R Package Version 0.2.2. Retrieved on 12 October 2020 https://cran.r-project.org/web/packages/frequencyConnectedness/frequencyConnectedness.pdf .

Luo, J., and S. Wang. 2019. "The Asymmetric High Frequency Volatility Transmission across International Stock Markets." *Finance Research Letters* 31: 104–109. doi:10.1016/j.frl.2019.04.025.

Maghyereh, A. I., B. Awartani, and E. Bouri. 2016. "The Directional Volatility Connectedness between Crude Oil and Equity Markets: New Evidence from Implied Volatility Indexes." *Energy Economics* 57: 78–93. doi:10.1016/j.eneco.2016.04.010.

Nicholson, W., D. Matteson, and J. Bien (2019). BigVAR: Dimension Reduction Methods for Multivariate Time Series. R package version 1.0.6. Retrieved on 12 October 2020 https://cran.r-project.org/web/packages/BigVAR/BigVAR.pdf .

Pesaran, M. H., and Y. Shin. 1998. "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58 (1): 17–29. doi:10.1016/S0165-1765(97)00214-0.

Shephard, N., and K. Sheppard. 2010. "Realising the Future: Forecasting with High Frequency-based Volatility (Heavy) Models." *Journal of Applied Econometrics* 25: 197–231. doi:10.1002/jae.1158.

Tibshirani, R. 1996. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society, Series B* 58 (1): 267–288.

Yoon, S. M., M. Al Mamun, G. S. Uddin, and S. H. Kang. 2019. "Network Connectedness and Net Spillover between Financial and Commodity Markets." *The North American Journal of Economics and Finance* 48: 801–818. doi:10.1016/j.najef.2018.08.012.

Appendices

Appendix 1. Variance Decomposition of Time-domain and Frequency-domain Analysis

Considering N variables structural VAR(p) model at $t = 1, \ldots, T$

$$x_t = \delta_1 x_{t-1} + \delta_2 x_{t-2} + \ldots + \delta_p x_{t-p} + \varepsilon_t$$

,

where x is the $Nx1$ vector of variables, δ is the NxNmatrices of coefficients and ε_t is white noise with the Σ covariance matrix. Rewriting the model with NxNmatrix lag-polynomial $\delta(L) = [I_N - \delta_1 L - \ldots - \delta_p L^p$, the model becomes $\delta(L)x_t = \varepsilon_t$. Next, $\delta(L) = [\Omega(\mathrm{L})]^{-1}$ and it is assumed that the roots of $|\delta(z)|$ are beyond the unit circle. Thus, demonstration of moving average ($MA(\infty)$) with VAR processing is

$$x_t = \Omega(\mathrm{L})\varepsilon_t$$

.

Pesaran and Shin (1998) introduced generalized variance decomposition which eliminates the possibility of variance decomposition dependence on VAR ordering. The contribution of variable l to the kth variable at h horizon, then generalized forecast error variance decomposition is

$$(\Theta_H)_{k,l} = \frac{\sigma_{ll}^{-1} \sum_{h=0}^{H} \left((\Omega_h \Sigma)_{k,l} \right)^2}{\sum_{h=0}^{H} (\Omega_h \Sigma \Omega_h')_{l,l}}$$

where σ_{ll} is the standard deviation of the error term, Ω_h is the moving average coefficients matrix ($N \times N$) at lag h. Note that the summation of each row of Θ_H is not equal to 1. Next, for the measure of connectedness and calculation of the spillover index from l to k at horizon H, variance decomposition is normalized $(\tilde{\Theta}_H)$ with constructions $\sum_{k=1}^{N} (\tilde{\Theta}_H)_{k,l} = 1$ and $\sum_{k=1}^{N} (\tilde{\Theta}_H)_{k,l} = \mathrm{N}$. For each variable, dividing with the summation of the row, $\tilde{\Theta}_H$ is

$$(\tilde{\Theta}_H)_{k,l} = \frac{(\Theta_H)_{k,l}}{\sum_{l=1}^{N} (\Theta_H)_{k,l}}.$$

In a simple way, sharing of variances from one variable to another and measuring this contribution with errors to forecast constructs measurement of connectedness. Thus, the proportional relation of the summation of off-diagonal variables to the sum of the whole matrix,

$$\varsigma_H = \frac{\sum_{k\neq 1} (\tilde{\Theta}_H)_{k,l}}{\sum^{\tilde{\Theta}_H}}$$

measure overall connectedness.

Next, with moving average coefficients Ω and $i = \sqrt{-1}$, Fourier transform of coefficients is $\Omega(e^{-i\omega}) = \sum_h e^{-i\omega h}\Omega_h$.

The generalized spectrum at a frequency ω, and lth element shock to the kth variable gives

$$(f(\omega))_{k,l} = \frac{\sigma_{ll}^{-1}\left|(\Omega(e^{i\omega})\Sigma)_{k,l}\right|^2}{\Sigma\Omega(e^{+i\omega}))_{l,l}}.$$

Definition of generalized variance decomposition on band d, with frequency band $d = (a, b) : a, b \in (-\pi, \pi)$ and $a < b$ is

$$(\Theta_d)_{k,l} = \frac{1}{2\pi}{}_d\, \zeta_k(\omega)(f(\omega))_{k,l}d\omega,$$

where $\zeta_k(\omega)$ is the weighting function with frequency band d scaled to $(\Theta_d)_{k,l}$ gives

$$(\tilde{\Theta}_d)_{k,l} = \frac{(\Theta_H)_{k,l}}{\sum_k (\Theta_\infty)_{k,l}},$$

where $(\Theta_\infty)_{k,l}$ represents $\sum_{d_s\in D} (\Theta_{d_s})_{k,l}$.

Within connectedness with frequency band d which provides exist connectedness influence within the frequency band and also solely weighted by the influence of series on defined frequency band is;

$$\varsigma_d^w = \left(1 - \frac{Tr\{(\tilde{\Theta}_d)\}}{\sum^(\tilde{\Theta}_d)}\right) \times 100.$$

Frequency connectedness on band d is;

$$\varsigma_d^f = \left(\frac{\sum^(\tilde{\Theta}_d)}{\sum^(\tilde{\Theta}_\infty)} - \frac{Tr\{(\tilde{\Theta}_d)\}}{\sum^(\tilde{\Theta}_d)}\right) \times 100,$$

where $tr\{\}$ is the trace operator.

Frequency connectedness divides the overall connectedness (ς_H) and gives ς_∞ when these parts are summed. Thus,

$$\varsigma_\infty = \sum_{d_s\in D} \varsigma_{d_s}^f$$

.

Appendix 2. Robustness of Time-Domain Connectedness Analysis

To eliminate the possibility of dependence on VAR order in variance decomposition, estimation is conducted within the framework of generalized VAR such as Diebold and Yilmaz (2012). However, sensitivity analysis is also applied according to their method. The sensitivity of the estimate is measured according to both the VAR orders and the forecast horizons. Thus, we check the robustness according to two to six VAR orders and 5, 10 and 15 days forecast horizons.

Figure 5 illustrates the robustness of the analysis according to VAR orders. In some periods range of minimum and maximum values obtained from two to six VAR order estimation results are higher than other periods. Besides the higher range especially in 2008–2009, the trend gives similar results.

Figure 6 shows the sensitivity of analysis with 5-day, 10-day, and 15-day forecast horizons. A robustness check for forecast horizon provides similar trend outcomes with all days.

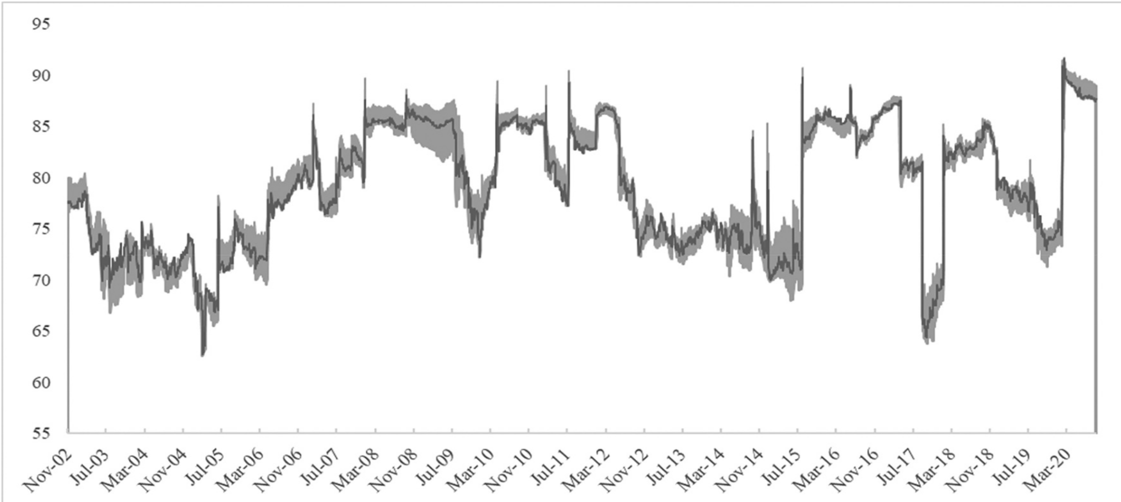

Figure 5. Sensitivity according to VAR orders. The light grey area represents min to max values total spillover range according to VAR order through two to six and the dark-grey line represents estimated (VAR order is 4) total spillover index in analysis, estimations are conducted with 200 rolling windows and 10-day forecast horizon.

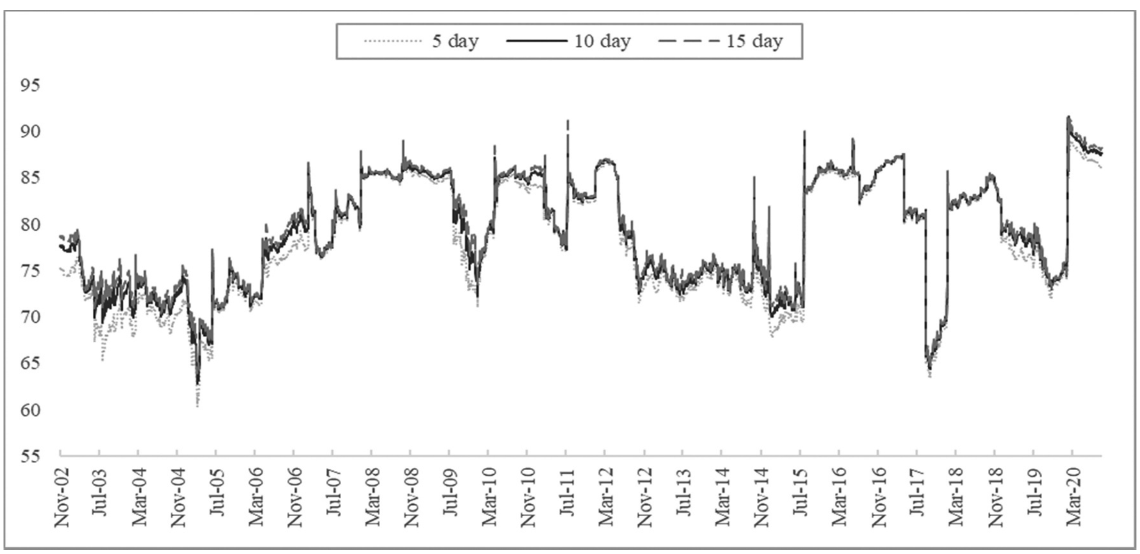

Figure 6. Sensitivity according to the forecast horizon. 200 rolling windows and VAR order is four.