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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

The comparison of range-based volatility estimators and an application of TVP-VAR-based connectedness

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Abstract

This paper aims to show the application of range-based volatility in connectedness analysis. For this purpose, we compare the volatility estimators Parkinson, Yang-Zhang, Garman-Klass, Rogers-Satchell, and modified Garman-Klass by Yang and Zhang methods. As an example, we calculated the range-based stock prices' volatility of four defense industry companies quoted in Borsa Istanbul. We compared the forecast performance of volatility against Heteroskedastic Root Mean Square Error statistics. We include the best-performing volatility series in the spillover analysis. Instead of the Cholesky decomposition VAR and generalized VAR approaches used in the calculation of the Diebold-Yılmaz connectedness index, we apply the TVP-VAR-based connectedness approach. The comparison results show that Rogers-Satchell for ASELSAN, KATMERLER, and PAPIL, and Parkinson volatility estimator for OTOKAR have the smallest error, respectively. The empirical findings of TVP-VAR connectedness show that the average forecast error variance of the network is 34.35%.

Keywords: Diebold-Yilmaz Connectedness, HRMSE, Range-based volatility, TVP-VAR.

JEL codes: C01,C11, C32, G11

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1. INTRODUCTION

The concept of volatility is defined in the literature as movements in the form of increases and decreases in the prices of financial assets. As a dictionary meaning, the concept of volatility is used in the sense of variability, but it can also be expressed as the standard deviation of the asset value under consideration. The inevitability of the momentary variability of risk factors is an extremely important situation in order to predict and work on the volatilities that are likely to be experienced in the future. Volatility is a natural consequence of the trade that takes place with the arrival of news and the later reactions of investors. The chain comovement of market players will push financial product prices to reach the equilibrium level after the information. The changing of expectations and related actions will be projected in the liquidity of a certain market. Since the information flow is continuous, volatility, information, and liquidity are expected to be connected. If the data holds more information when estimating volatility, forecast results can be more consistent.

One can model the volatility by applying various time series analysis methods. Poon and Granger (2003, 2005) divide volatility models into three groups. These groups are Stochastic Volatility models, Predictions Models via historical standard deviations, and Conditional Volatility estimated by ARCH-type models. We consider the range-based volatility estimators, in other words, volatility indicators using Open-High-Low-Close (OHLC) prices. Li and Hong (2011) state that range-based volatility estimators are 5–14 times more efficient with respect to forecasting error measures. In addition, these kinds of volatility estimators have a simple structure to implement. In fact, the range is reported as candlestick plots which are used widely in technical analysis. Although range-based estimators have calculation and simplicity advantages, they are not studied enough in the literature. One can state that range-based estimators have poor performance in empirical studies, therefore there is a gap in the literature on the range-based volatility approach. Chou (2005) introduced the Conditional Autoregressive Range (CARR) model to the literature. The CARR models use the idea of well-known GARCH models to examine the dynamic nature of the adjusted range. He also claims that the fundamental reason for the poor performance of range-based approaches is that they are not so successful and adequate models to capture the dynamics of volatilities. We do not consider the CARR model in this study. This paper covers the high-low-based Parkinson (1980) estimator as well as OHLC estimators Garman and Klass -GK- (1980), Rogers and Satchell -RS- (1991), Yang and Zhang -YZ- (2000), modified Garman and Klass by Yang and Zhang -GKYZ- when estimating volatility. There are few studies about the comparison of the range-based volatility estimators' performance. Yarovaya et al, (2016) examine the GK, Park, and RS, they obtain inconclusive outcomes. Even though all the mentioned range-based volatility estimators have different characteristics, one can figure out that there are no certain results in the literature about which estimator performs more accurately. Arnerić et al (2019) find no exact result for the comparison. They use two different metrics to calculate the forecast error. But one of the error measures indicates the Garman–Klass estimator is more adequate, while the other one signs the Yang–Zhang estimator. They conclude when comparison results cannot make a clear conclusion about the efficiency of estimators, one can apply the tail dependence error measure to determine the last decision of ordering. Raju and Rangaswamy (2017) measure the in-sample and out-of-sample forecasting error of volatility estimators and find that YZ is the most adequate estimator with respect to error metrics.GK approach is to be found as the optimal OHLC estimator in the studies of Li and Hing (2011), Bali and Weinbaum (2005), Todorova and Husmann (2012), and Jiang et al (2014).

In addition to measuring the volatility in the markets, understanding the relationships between different financial markets are important for portfolio diversification, portfolio optimization, risk management, hedging, and investment decisions. If the return or volatility spillover among financial assets increases, the possibility of diversification decreases. With the increase in the amount of information flow, the spread of volatility between the stock markets has increased. Inter-market risk contamination can often be caused by a financial crisis. The spillover effect between markets is one of the main factors that determine the predictability of financial markets. The importance of spillover analysis has emerged from the fact that markets around the world are interconnected. In general, volatility increases sharply during financial crises, and it may naturally be possible to measure and monitor such spillovers so that crises can be monitored by providing early warning systems. Measuring and estimating the volatility spread is related to the effort to estimate the level of risk and uncertainty of the relevant market or financial instrument.

Therefore, we apply the method of volatility connectedness based on the Diebold and Yilmaz - DY - (2009) approach which allows asymmetries in bilateral connections between markets DY propose the connectedness as a directional measure of volatility spillover. DY calculate a Connectedness Index (DYCI) which is used to interpret the impact of shocks from other financial assets within the estimation error variance of each financial asset. DYCI is a computational tool to figure out the spread trends, cycles, and bursts of the return volatility of assets, asset portfolios, and asset markets both within and between countries. In addition, connectedness measurement is potentially useful to monitor crises, because connectedness generally tends to increase sharply during crises.

VAR-based interconnectedness approaches have been utilized to understand the subjects which are related to interdependencies and volatility spillovers of financial markets (Diebold & Yilmaz 2009, 2012, 2014). DY make it easy to measure the interdependence over a network of variables. Furthermore, this method yields results for total, directional, and net interdependence. The obtained results of the DY approach provide us with determining the type of interdependence and detailed knowledge. More specifically, in the case of net interdependence, we can easily separate which financial assets are net shock transmitters and net shock receivers. So, one can easily figure out the underlying dynamics. Using the dynamic structure of the method helps to reach the policy implications.

Diebold-Yilmaz (2009, 2012) uses a VAR framework with Cholesky decomposition and a generalized VAR approach, respectively. DY2009 has been insufficient to examine the necessity of ranking the variables and the spread between different types of asset markets. Therefore, Diebold-Yilmaz (2012) includes a generalized VAR approach in which the variables can be ordered in an irrelevant way. Finally, Diebold-Yilmaz (2014) emphasizes the concept of connectivity and enables a more accurate determination of potential changes in parameter values. This approach brings two innovations these are about the effect of outliers and arbitrary rolling window size. One does not need to identify the arbitrary rolling window size and the effect of outliers disappears. Thus, the dynamic measures can be calculated without the loss of observations. Generalized versions of these studies are available in Diebold-Yilmaz (2015) and an application in Diebold-Yilmaz (2016). However, the rolling-window VAR model is insufficient in some aspects, in this context Antonakakis & Gabauer (2017) and Korobilis &Yilmaz (2018) develop a connectedness model based on the Time-Varying Parameter Vector Autoregression (TVP-VAR) model. In general, the response of the rolling-window-VAR approach to the events is occurred as either overreacting or softening the effect. But we can observe that the reaction of the TVP-VAR-based connectedness model is adapting instantly. In addition, the TVP-VAR model is a solution for arbitrarily chosen rolling window size. Thus, it prevents the loss of observed data and satisfies the regularity of the parameters. Later, Antonakakis et al. (2020) introduce a method for constructing confidence intervals of dynamic connectedness. They combine bootstrapped generalized impulse-response functions with common confidence intervals for impulse-response functions. Additionally, they provide an uncertainty estimate of TVP-VAR-based connectedness measures, allowing forgetting factors and random variation of Minnesota priorities.

In this study, we first make a comparison between the range-based volatility estimators and examine the pass-through between the obtained volatilities applying the TVP-VAR-based Diebold-Yilmaz Connectedness approach. For illustrative purposes, we chose defense industry companies because of Turkey's rapid development in this field. In particular, the use of Turkish Defense Industry products in the current armed conflicts in Turkey's immediate surroundings and the global interest in these products motivated us to choose these stocks. Therefore, we estimate the volatility of the stock prices of four defense industry companies quoted on Borsa Istanbul using the OHLC values. Then, we calculate DYCI to interpret the volatility spillover between the stocks. This study consists of the following parts. The first part is the introductory part, which includes conceptual explanations and literature. The second and the third part cover methods and materials. These parts consist of sections that describe range-based volatility estimators and the TVP-VAR Connectedness approach. The following section introduces the volatility dataset. In the third section, the findings obtained from the connectedness approach are available. The last section concludes the paper.

2. VOLATILITY MODELS

2.1. Range-Based Volatility Estimators

Intraday Open-High-Low-Close (OHLC) prices are commonly used in volatility calculations in technical analysis indicators. These volatility calculation approaches have several advantages over volatility calculations based on closing prices. Before moving on to OHLC volatility estimators, we can express the classic close-to-close (CC) volatility estimator as follows:

$$\sigma_{cl} = \sqrt{\frac{Z}{n-2}\sum_{i=1}^{n-1}(r_i - \bar{r})^2}$$

where $r_i = log\left(\frac{C_i}{C_{i-1}}\right)$ is a log-return of closing prices (C_i) and (C_i) and $\bar{r} = \frac{r_1+r_2+\cdots+r_{n-1}}{n-1}$. n is the number of historical days used in the volatility estimate and Z is the number of closing prices in a year. We use the high-low-based Parkinson (1980) estimator as well as OHLC estimators Garman and Klass (1980), Rogers and Satchell (1991), Yang and Zhang (2000), Garman and Klass - Yang and Zhang when estimating volatility. These volatility estimators for n and Z are as follows:

1. Parkinson (1980) introduced the approach for estimating volatility based on high and low prices. So, the formula is

$$\sigma_{PARK} = \sqrt{\frac{Z}{4n\times log2}\sum_{i=1}^{n}\left(log\frac{H_i}{L_i}\right)^2} \quad (1)$$

2. Garman and Klass (1980) developed the estimation method under two assumptions which are Brownian motion with zero drift and no opening jumps. No opening jumps means the opening price is equal to close of the previous period. The comparison results indicate that the efficiency of the GK estimator is 7.4 times the CC estimator's efficiency. The euation of GK is

$$\sigma_{GK} = \sqrt{\frac{Z}{n}\sum_{i=1}^{n}\left(\frac{1}{2}\left(log\frac{H_i}{L_i}\right)^2 - (2log2-1)\left(log\frac{C_i}{O_i}\right)^2\right)} \quad (2)$$

3. Roger and Satchell (1991) also assumed no opening jump in their estimator, but differently from GK, they allow non-zero drift in the volatility estimator. They apply the following formula

$$\sigma_{RS} = \sqrt{\frac{Z}{n}\sum_{i=1}^{n}\left(log\frac{H_i}{C_i}\times log\frac{H_i}{O_i} + log\frac{L_i}{C_i}\times log\frac{L_i}{O_i}\right)} \quad (3)$$

4. Yang and Zhang extend the Garman Glass volatility estimator allowing for opening jumps. In addition, the estimator assumes Brownian motion with zero drift. This method is one of the most preferable estimators among the OHLC volatility estimators for zero drift. Its efficiency is 8.0 times of the classic CC estimator. But it has a disadvantage when the drift is nonzero but instead relatively large to the volatility. It will tend to overestimate the volatility. One can express it using the following equation

$$\sigma_{GKYZ} = \sqrt{\frac{Z}{n}\sum_{i=1}^{n}\left(\left(log\frac{O_i}{C_{i-1}}\right)^2 + \frac{1}{2}\left(log\frac{H_i}{L_i}\right)^2 - (2log2-1)\left(log\frac{C_i}{O_i}\right)^2\right)} \quad (4)$$

5. Yang and Zhang's (YZ) approach has a minimum estimation error. This estimator is independent both of the drift and opening gaps. Moreover, the efficiency of the YZ estimator is maximally 14 times the CC estimator's efficiency. One can interpret it as a weighted average of the RS estimator. The performance of YZ may reduce to the CC estimator if the price process is heavily dominated by opening jumps. YZ can be applied using the following formulations

$$\sigma_{YZ} = \sqrt{\sigma_0^2 + k\sigma_c^2 + (1-k)\sigma_{RS}^2} \tag{5}$$

where

$$\sigma_0^2 = \frac{Z}{n-1}\sum_{i=1}^{n}\left(log\frac{O_i}{C_{i-1}} - \mu_0\right)^2$$

$$\mu_0 = \frac{1}{n}\sum_{i=1}^{n} log\frac{O_i}{C_{i-1}}$$

$$\sigma_c^2 = \frac{Z}{n-1}\sum_{i=1}^{n}\left(log\frac{C_i}{O_i} - \mu_c\right)^2$$

$$\mu_c = \frac{1}{n}\sum_{i=1}^{n} log\frac{C_i}{O_i}$$

$$\sigma_{RS}^2 = \frac{Z}{n}\sum_{i=1}^{n}\left(log\frac{H_i}{C_i}\times log\frac{H_i}{O_i} + log\frac{L_i}{C_i}\times log\frac{L_i}{O_i}\right)$$

2.2. Data Set

The data set consists of stock prices of four defense industry companies listed on Borsa Istanbul. The stocks used in the analysis are ASELSAN, KATMERLER, OTOKAR and PAPİL. Since PAPİL stock started to be traded on BIST on 29 November 2019, data covers daily OHLC prices from 2020-01-02 to 2022-06-01. The dataset is obtained from the "Yahoo Finance" platform via the 'quantmod' R package (Ryan & Ulrich, 2020). The close prices are adjusted for all applicable splits and dividend distributions in YahooFinance. Therefore, the open, high, and low prices are also adjusted for splits and dividend distributions. Moreover, the raw data may contain missing values. In our case, all stocks' price data have the missing values on the same date. So, we didn't need to remove any observations.

2.3. The Comparison Results of Range-Based Volatility Estimators

Although Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are very common metrics to compare the forecasting performance we apply Heteroskedastic Root Mean Square Error (HRMSE) to compare the out-of-sample forecasting performance of the volatility estimators. When volatility clustering occurs, RMSE and MAE are generally not sufficient and proper metrics for accurate model comparison (Bayraci & Ünal, 2014). The HRMSE computes the error measures as an average relative error. Moreover, it takes high and low volatility periods into account (Bayraci & Ünal, 2014; Bollen, 2014). Therefore, we utilize HRMSE to compare the volatility methods. The error statistics can be computed using the following formula

$$HRMSE = \left(\frac{1}{n}\sum_{t=1}^{n}\left(\frac{\sigma_t}{\hat{\sigma}_t} - 1\right)^2\right)^{1/2} \tag{6}$$

Table 1 shows the HMRSE statistical results. The results show that RS for ASELSAN, KATMERLER and PAPİL, and Parkinson volatility estimator for OTOKAR have the smallest error, respectively.

Table 1. The Comparison of Range-Based Volatility Estimators

Range-Based Volatility Estimator	ASELSAN	KATMERLER	OTOKAR	PAPİL
Garman and Klass	0.9407214	0.9434485	0.9444576	0.9433979
Parkinson	0.9418122	0.9434276	***0.9441477***	0.9434275
Rogers and Satchell	***0.9399920***	***0.9433925***	0.9453977	***0.9433702***
Yang and Zhang	0.944069	0.9496686	0.9473703	0.9461385
Garman&Klass – Yang&Zhang	0.9443705	0.9499457	0.9471353	0.9463432

Source: Authors' own calculations

Figure 1 presents the range-based volatility series. The skewness and the excess kurtosis statistics in Table 2 indicate that all the volatility series have significant skewness and excess kurtosis with respect to the normal distribution. Jarque-Bera test statistics also indicate the series are not normally distributed at the 1% significance level. Therefore, we can apply Elliot-Rothenberg-Stock (ERS) test to check for stationarity of the volatility series. ERS statistics show that all volatility series are stationary.

There is a significant autocorrelation that emerges in all series and the square series. So, the mean and variance of each series change over time. Therefore, the TVP-VAR model with a time-varying variance-covariance structure is an appropriate econometric framework that captures all these factors. Moreover, Table 1 shows

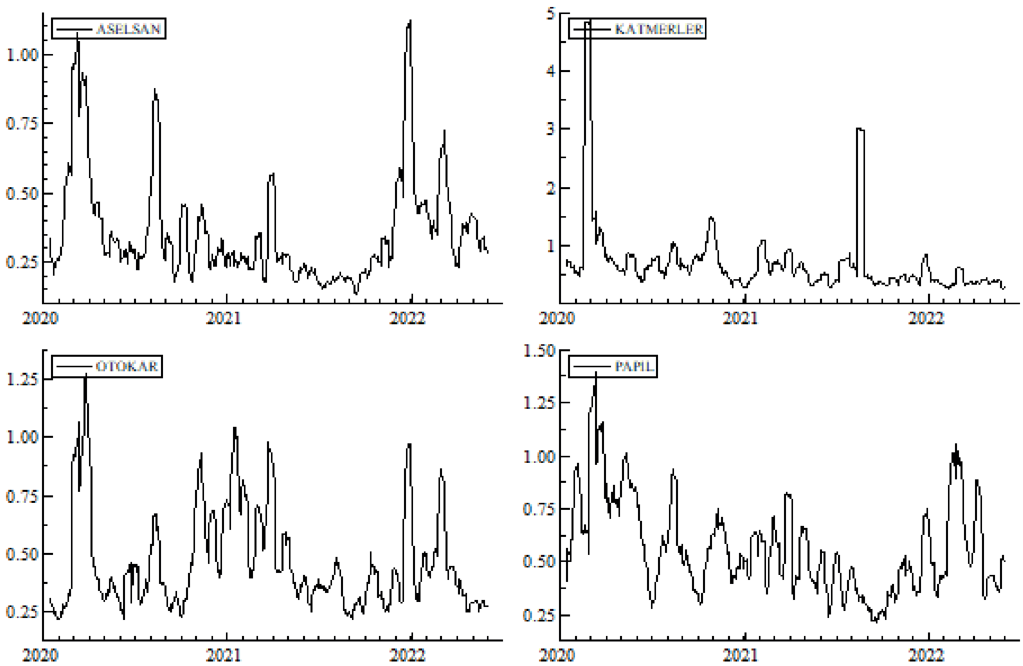

Figure 1. Range-Based Volatility Series

Table 2. Summary Statistics

Statistics	**ASELSAN**	**KATMERLER**	**OTOKAR**	**PAPIL**
Mean	0.364	0.703	0.472	0.569
Variance	0.039	0.451	0.048	0.051
Skewness	1.839***	4.581***	1.246***	0.953***
Ex.Kurtosis	3.206***	23.440***	0.748***	0.658***
JB	589.267***	15675.527***	167.590***	100.706***
ERS	-4.191***	-5.503***	-3.765***	-3.485***
Q(10)	2367.653***	1601.338***	2149.838***	2247.574***
Q2(10)	2206.552***	1424.183***	2018.880***	2182.663***
Pearson Correlation Matrix				
ASELSAN	1.00			
KATMERLER	0.271***	1.00		
OTOKAR	0.564***	0.122***	1.00	
PAPIL	0.610***	0.198***	0.525***	1.00

Notes: *** p < .01. Skewness, Kurtosis, and JB: Jarque and Bera test for normality; ERS: Elliott-Rothenberg-Stock unit-root test; (20) and *Q*2(20): weighted portmanteau test. **Source:** Authors' own calculations the unconditional correlation matrix across the range-based volatility series of defense industry firms' stocks over the sampling period. Pearson correlations show that there is a significant positive correlation between the volatilities. The highest correlation occurs between ASELSAN and PAPIL volatilities.

3. RANGE-BASED VOLATILITY CONNECTEDNESS

Antonakakis et al. (2020) use the TVP-VAR method to enhance Diebold and Yilmaz's (2014) proposed connectedness approach. They allow the variance-covariance matrix to fluctuate using a Kalman filter estimation with forgetting factors. They follow the study of Koop and Korobilis (2013, 2014) to determine the VAR and EWMA forgetting factors. To investigate the time-varying linkage between price volatilities of defense industry stocks, we estimate TVP-VAR(2) model, which is determined to be the most appropriate by Bayes Information Criteria (BIC), is as follows

$$y_t = A_t z_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{7}$$

$$vec(A_t) = vec(A_{t-1}) + \upsilon_t \qquad \upsilon_t \sim N(0, S_t) \tag{8}$$

where y_t and z_{t-1} represent $k \times 1$ and $2k \times 1$ vectors, respectively, A_t is $k \times 2k$ is dimensional matrix, and ϵ_t and υ_t are $k \times 1$ and $2k^2 \times 1$ dimensional vectors, respectively. Σ_t and S_t are time-varying variance-covariance matrices of which dimensions are $k \times k$ and $2k^2 \times 2k^2$, respectively. Finally, $vec(A_t)$ is a $2k^2 \times 1$ is a dimensional vector.

Diebold-Yilmaz's approach is based on the Generalized Forecast Error Variance Decomposition (GFEVD) analysis. The transformation of TVP-VAR into TVP-VMA is $y_t = \sum_{h=0}^{\infty} A_{ht}\epsilon_{t-h}$ where $A_0 = I_k$. So, the influence of a shock in variable j on variable i is computed as:

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\sum_{h=0}^{H-1}\left(\epsilon_i^T A_{ht}\Sigma_t\epsilon_j\right)^2}{\left(\epsilon_i^T\Sigma_t\epsilon_j\right)\sum_{h=0}^{H-1}\left(\epsilon_i^T A_h\Sigma_t A_{ht}^T\epsilon_i\right)} \tag{9}$$

with and . Thus, the connectedness measures of Diebold-Yilmaz (2012, 2014) via GFEVD are calculated as follows

Total Directional Connectedness to Others (TO)

$$TO_{jt} = \sum_{i=1,i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \tag{10}$$

Total Directional Connectedness from Others (FROM)

$$FROM_{jt} = \sum_{i=1,i\neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) \tag{11}$$

Net Total Directional Connectedness (NET)

$$NET_{jt} = \sum_{i=1,i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) - \sum_{i=1,i\neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) \tag{12}$$

$$NET_{jt} = TO_{jt} - FROM_{jt}$$

Total Connectedness Index (TCI)

$$TCI_t = k^{-1}\sum_{j=1}^{k} TO_{jt} \equiv k^{-1}\sum_{j=1}^{k} FROM_{jt} \tag{13}$$

Net Pairwise Directional Connectedness (NPDC)

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}^{g}(H) - \tilde{\phi}_{ji,t}^{g}(H) \tag{14}$$

3.1. Empirical Findings of TVP-VAR Connectedness

We follow the studies by Koop and Korobilis (2014), Korobilis and Yilmaz (2018), and Antonakakis et al (2020) to figure out the forgetting factors and prior distribution. We set TVP-VAR forgetting factor as 0.99 and the EWMA forgetting factor as 0.99. Also, we assume Minnesota Prior for TVP-VAR model.

Table 3. Average Volatility Connectedness Table

	ASELSAN	KATMERLER	OTOKAR	PAPIL	FROM
ASELSAN	57.07	7.04	19.4	16.48	42.93
KATMERLER	3.45	90.41	2.3	3.83	9.59
OTOKAR	23.04	3.43	61.86	11.67	38.14
PAPİL	23.6	6.95	16.18	53.27	46.73
TO	50.09	17.43	37.88	31.99	137.39
Inc.Own	107.17	107.84	99.74	85.26	**cTCI/TCI**
NET	7.17	7.84	-0.26	-14.74	45.80/34.35

Notes: Results are based on a TVP-VAR (2) model and a 10-step-ahead GFEVD. **Source:** Authors' own calculations

The Total Connectedness Index (TCI) shows the average impact of a shock to one financial asset on other assets in the network. A relatively high TCI index value indicates that the spillover of a shock in a variable will be significant. In this case, the interconnectedness of the market increases the risk. The relatively low TCI value indicates that most variables in the network are independent. Thus, it means that the shock that will occur in one of the variables will have a weak effect on any adjustment movement in the other variables. Hence, it will result in lower market risk. Table 3 presents the average connectedness measures. The rows of the 4x4 (blue) matrix in Table 3 contain the FROM connectedness and the columns contain the TO connectedness values. The difference between To and FROM gives the NET connectedness values that are available at the end of Table 3. The main diagonal of the matrix consists of the variance shares of the variables themselves. The off-diagonal elements reflect the interaction between financial assets. First, we sign that there is a relatively medium connectedness between volatilities. We find that TCI is 34.35%. So, we can interpret that the interconnectedness in the network causes 34.35% of the total forecast error variance on average. Figure 2 illustrates the dynamic connectedness throughout the whole period. Thus, certain periods that affect adherence among volatilities over time can be identified. For example, the highest connectedness occurs in the first quarter of 2020, when the Covid-19 pandemic was declared by Worl Health Organization.

TCI reaches its highest value of 47.18% on 2020-02-05 and becomes 40.83% at the time of the first Covid-19 case in Turkey. Interestingly, in June 2021, the TCI value starts to rise again and reaches 42.45% on 2021-06-25. This is due to the emergence of the delta variant, which is more contagious despite the availability of a vaccine against the Covid-19 virus. It will not cause an increase in the TCI value of October 2020, the period when the Nagorno-Karabakh War ended with the victory of Azerbaijan.

Net Total Directional Connectedness (NET) is calculated by subtracting the effect of variable j on others from the effect of others on j shows whether the variable is a net shock transmitter or receiver. If $NET_{jt} > 0$ $(NET_{jt} < 0)$, the variable j is a net transmitter of shocks ($receiver$) – and therefore drives the network ($driven\ by$).

Figure 3 presents the NET of the system. The positive values of the shaded area show a net-transmitting role of the index and negative values show the period when the index is a net receiver of shocks from others.

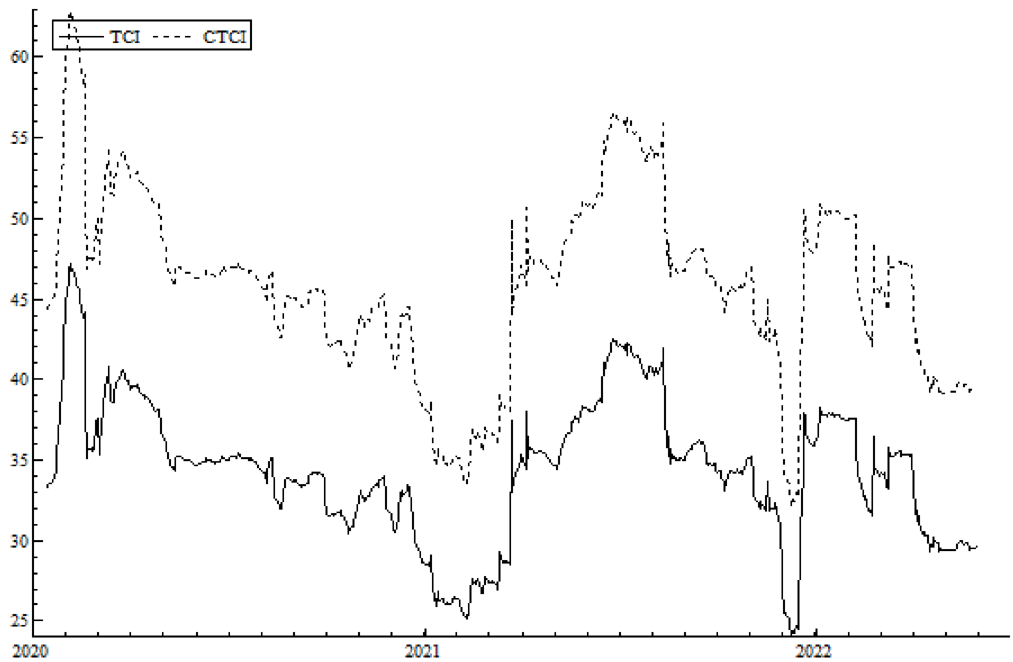

Figure 2. Dynamic Total Connectedness Index

Notes: cTCI is Corrected TCI. Results are based on a TVP-VAR (2) model and a 10-step-ahead GFEVD.

PAPIL is a risk receiver throughout the entire period. It is the stock that is most affected by the high volatility spillover especially when the Covid-19 pandemic started. PAPIL is affected by up to 46% of the GEFVD created by the shocks in other stocks. The highest volatility transmitter of this period is KATMERLER. While the extreme volatility in exchange rates in December 2022 made ASELSAN and KATMERLER shock receivers, its effect is more visible in PAPIL.

The Net Pairwise Directional Connectedness (NPDC) offers information about the bilateral relationship between j and i via subtracting the impact variable j has on variable i by the influence variable i has on variable j. If $NPDC_{ij,t} > 0$ ($NPDC_{ij,t} < 0$), it means that the variable j dominates (*is dominated by*) the variable i. Figure 4 presents NPDC measures of spillovers. Although the NPDC plots do not clearly reveal which stock is more dominant, we see

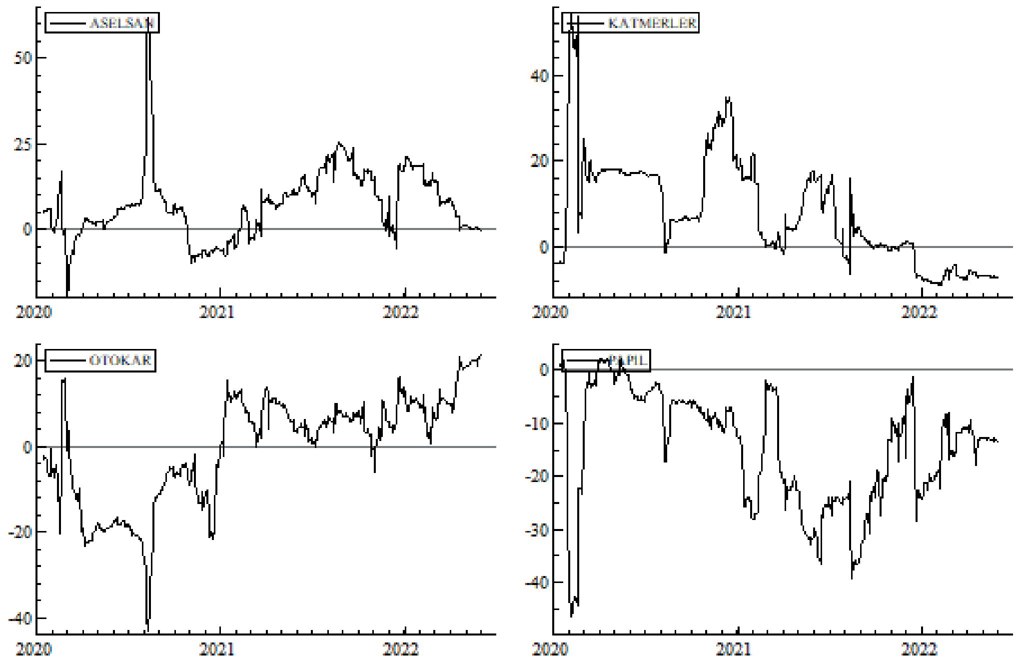

Figure 3. Net Total Directional Connectedness

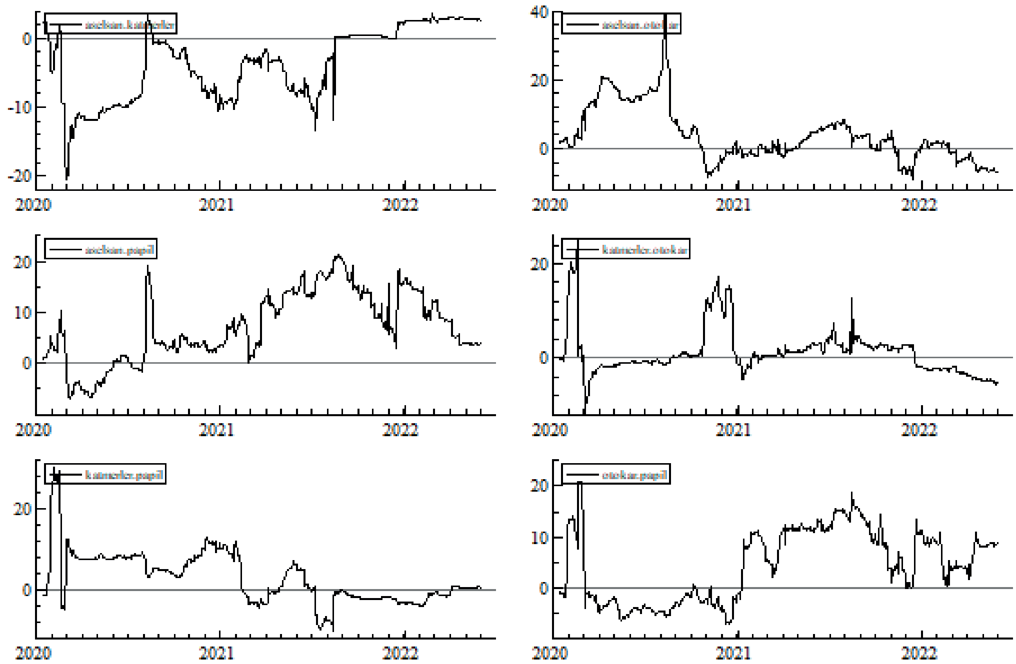

Figure 4. Net Pairwise Directional Connectedness

that OTOKAR has been dominant against PAPİL since the beginning of 2021. We understand that KATMERLER is dominant against PAPİL until the beginning of 2021. ASELSAN, on the other hand, appears to be dominant against PAPİL after the third quarter of 2020.

4. CONCLUSION

This study demonstrates the use of range-based volatilities, also known as OHLC-based, in the analysis of connectivity. For this purpose, we first introduced the volatility estimators Parkinson, Garman and Klass (GK), Rogers and Satchell (RS-), Yang and Zhang (YZ), and modified Garman and Klass by Yang and Zhang (GKYZ). As an example, we calculated the range-based volatility of the stock prices of four defense industry companies quoted on Borsa Istanbul. We compared the forecast performance of the volatilities according to the HRMSE statistics. The best-performing volatility series were included in the connectedness analysis. Instead of the Cholesky decomposition VAR and generalized VAR approaches used by Diebold-Yilmaz (2009, 0212,2014), we applied the TVP-VAR-based connectedness approach developed by Antonakakis et al (2020). We can say that the most important advantage of the TVP-VAR approach is that it is unnecessary to specify a certain rolling-window size and data loss does not occur. In conclusion, our findings show that Rogers-Satchell for ASELSAN, KATMERLER, and PAPIL, and Parkinson volatility estimator for OTOKAR have the smallest error, respectively. Moreover, the empirical findings of TVP-VAR connectedness show that the average forecast error variance of the network is 34.35%. The reason for using an HRMSE metric in our comparison between volatility estimators is that the other error metrics do not give accurate results during the volatility cluster periods. One can apply various metrics by adding Root Mean Square Error, Mean Absolute Error, and Heteroskedastic Mean Absolute Error to compare the out-of-sample forecasting performance of the volatility models. One can extend the analysis to utilize the frequency connectedness and quartile VAR connectedness methods.

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