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VOLATILITY SPILLOVERS EFFECT ANALYSIS DURING COVID-19 PERIOD USING EWMA MODEL: THE CASE OF HEALTH SECTOR STOCKS IN ISE

Yakup ARI [1]

Abstract

The importance of the health sector is once again understood by the emergence of the Covid-19 pandemic. The purpose of this study is to examine the volatility spillover effect between health sector stocks traded in Istanbul Stock Exchange and exchange rate and precious metal prices during the pre-Covid-19 period and the Covid-19 period. For this purpose, the volatility of returns of four health sector stocks traded on the Istanbul Stock Exchange, foreign exchange rate, and the price of gold were obtained using the Exponential Weighted Moving Average model and used in the Diebold-Yılmaz Spillover Index approach. The data set is divided into two periods according to the date of the first cases seen in Turkey. While the first period consisted of 267 observations between January 2, 2019, and February 28, 2020, the second period consisting of 267 observations was created between March 2, 2020, and April 1, 2021. According to the results, the total spillover index in the period before Covid-19 is 9.60%, which indicates a low connectedness between markets. The spillover index for the Covid-19 period is calculated at 21.90% which means the error variances in markets are on average 21.90% originated from other markets. Moreover, it is found that RTA Laboratories has the highest net spillover in the Covid-19 period.

Keywords **:** *Covid-19, Dieobold-Yılmaz Index, EWMA model, Volatility spillover.*

JEL Classification *: C18, C58, G01, G15, Q02.*

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EWMA MODELİ KULLANARAK COVİD-19 DÖNEMİ OYNAKLIK YAYILIM ETKİSİ ANALİZİ: BİST SAĞLIK SEKTÖRÜ HİSSE SENETLERİ ÖRNEĞİ

Öz

Sağlık sektörünün önemi Covid-19 pandemisinin ortaya çıkmasıyla bir kez daha anlaşılmıştır.. Bu çalışmanın amacı, Borsa İstanbul'da işlem gören sağlık sektörü hisse senetleri ile döviz kuru ve kıymetli maden fiyatları arasındaki volatilite yayılma etkisini Covid-19 öncesi ve Covid-19 döneminde incelemektir. Bu amaçla İstanbul Menkul Kıymetler Borsası'nda işlem gören dört sağlık sektörü hissesinin getirileri, döviz kuru ve altın fiyatının oynaklığı Üstel Ağırlıklı Hareketli Ortalama modeli kullanılarak elde edilmiş ve Diebold-Yılmaz Yayılma Endeksi yaklaşımında kullanılmıştır. Veri seti, Türkiye'de görülen ilk vakaların tarihlerine göre iki döneme ayrılmıştır. İlk dönem 2 Ocak 2019 ile 28 Şubat 2020 tarihleri arasında 267 gözlemden oluşurken, 2 Mart 2020 ile 1 Nisan 2021 tarihleri arasında 267 gözlemden oluşan ikinci dönem oluşturulmuştur. Sonuçlara göre toplam yayılma endeksi, Covid-19 öncesi dönemde %9.60, bu da piyasalar arasında düşük bağlantılılığa işaret etmektedir. Covid-19 dönemi için yayılma endeksi %21,90 olarak hesaplanmıştır, yani piyasalardaki hata varyanslarının ortalama %21,90'ı diğer piyasalardan kaynaklanmaktadır. Ayrıca RTA Laboratuvarları hisse senedinin Covid-19 döneminde en yüksek net oynaklık yayılımına sahip olduğu tespit edilmiştir.

Anahtar Kelimeler ***:*** *Covid-19, Dieobold-Yılmaz Endeksi, EWMA Modeli, Oynaklık Yayılımı.*

Jel Sınıflandırması ***:*** *C18, C58, G01, G15, Q02.*

INTRODUCTION

The concept of volatility can be defined as the fluctuation of a variable in a certain period by deviating from its expected value. Financial volatility is defined as the measure of the variability in the value of a financial asset, indicator, or index within a certain period. Financial volatility is important for financial markets as it is an indicator of the risk level. Investors want to make correct and reliable decisions by using different transactions and investment opportunities in the capital markets every day. Therefore, investors in capital markets must predict and analyze the volatility accurately and reliably. Because, because of unexpected events, sudden decreases and increases are experienced in the prices of financial assets in capital markets. Movement in financial assets and the effect of this movement on volatility pose a significant risk for investors. It is not possible to prevent the risks that will occur with the developing technological opportunities. However, investors can the opportunity to create a systematic and effective portfolio strategy by accurately predicting volatility. It is necessary to determine the volatility and examine the factors that affect the volatility to ensure an efficient portfolio management process and achieve the desired return levels. The shocks and fluctuations in the international capital markets have gradually caused the risk factor to spillover rapidly in recent years. The importance of determining the variables related to the instruments traded in the capital markets and accurately predicting the shocks that will occur in the financial markets is increasing day by day for investors to avoid risk and make a profit. This situation has further increased its importance with the onset of the Covid-19 global pandemic.

Identifying volatility spillover is very important for investors. Especially international portfolio investors should closely follow the volatility transmission between developed and emerging markets. Because if the volatility spillover between the mentioned markets is weak, a shock to be experienced in emerging markets will affect the emerging markets less. In this case, investors in developed markets can reduce their risks by diversifying by investing in emerging markets. Apart from stock markets, volatility spillovers can also occur between futures markets, financial assets such as bonds, macroeconomic variables such as exchange rates, interest rates, indices, and indicators. In other words, spillovers are effective on many different economic and financial variables (Li & Giles, 2015).

Volatility and volatility spillover conceptually form the basis for measuring market risk. These concepts can be used to clarify and examine the connectedness that may occur between markets. According to Diebold and Yılmaz (2015), risk measurement is an essential component of successful risk management. Therefore, great attention and resources have been devoted to measuring various financial risks. It can occur in portfolio value because of the risks posed by the underlying assets that make up a portfolio. The risk of change in the portfolio value is the most fundamental element that constitutes the market risk. The risk of a portfolio is not a weighted sum of the risks of its components. The overall portfolio risk depends on how the pieces interact – how and how they are connected. The probability of extreme market movements, often associated with all or most of the assets moving in the same direction, depends on connectivity. Connectedness in financial contexts goes beyond risk assessments, at least as traditionally conceptualized, and certain types of connectedness may be directly desired. For example, connectedness can arise from and vary from risk-sharing through insurance, linkages between resources, and use of funds as savings are channeled into investments, comparative advantage models that create international trade, regional and global capital market integration, and enhanced coordination. global financial regulation and accounting standards.

The importance of the health sector is once again understood by the emergence of the Covid-19 pandemic. In this period, all companies working in the field of health services, health technology, and pharmacology have become the center of attention. Vaccination studies against Covid-19 have increased the importance of national or international companies in the field of biochemistry and pharmacology. The shares of health sector companies operating in these areas and listed on the stock exchange have increased their weight in investors' portfolios. In this context, stock returns and volatilities of health sector companies listed on the Istanbul Stock Exchange (ISE) are issues that need to be examined.

Macroeconomic problems such as rising unemployment rates, high inflation, and fluctuations in the exchange rate affect the Turkish financial markets. Therefore, uncertainties and volatility in Turkish financial markets have increased in recent years. It has been seen that increasing uncertainties and risks in all world financial markets affect stock market investments with the onset of the global Covid-19 pandemic. Investors started to turn to alternative investments other than stock markets. Especially the interest in the cryptocurrency markets can be considered as proof of this situation. It can be said that the interest of investors, also in Turkish markets, has shifted from the stock market to other markets. The rate of foreign investors in the ISE has declined to around forty percent. In this environment where domestic and foreign investors have started to turn to different investment areas, exchange rates, precious metals, and cryptocurrencies are the prominent investment areas. Cryptocurrencies are not included in this study, and the US Dollar - Turkish Lira (USD-TRY) exchange rate and gram gold prices in Turkish Lira (GAU-TRY) are included.

Interest in companies that conduct vaccine or drug studies has increased in Turkey as well as in the world with the emergence of vaccines developed against the COVID-19 virus. The focus of this study is on the volatility spillovers between health sector companies traded in Istanbul Stock Exchange (ISE) and mentioned investment tools. The stocks included in the study are as follows; Deva Holding (DEVA), Eczacıbaşı İlac (ECILC), RTA Laboratuvarlari (RTALB) and Seyitler Kimya (SEYKM). The stocks of companies newly listed on the stock exchange and companies operating in the field of health services are not included in the study.

For this purpose, stock volatility and the volatility spillover between USD-TRY and GAU-TRY are analyzed using the Diebold-Yilmaz (2009, 2012 and 2014) approach (Henceforth abbreviation DY denotes the Diebold-Yılmaz). The volatilities of the specified variables are obtained by the EWMA (Exponentially Weighted Moving Average) model. The general structure of the study is designed as follows. The following section will include a brief literature review, followed by methodology sections. In the fourth section, empirical findings will be given, and the results will be presented with a short discussion in the last section.

I. BRIEF LITERATURE REVIEW

There are many studies examining the relationships between ISE indices and other financial markets. This section includes volatility spillover studies on the ISE, the foreign exchange market, and precious metals, as most of the studies available in the literature are not stock based. Some of the studies that examine these relationships through the concept of volatility can be briefly listed as follows.

In the study of Değirmenci et al. (2017), the volatility spillover of the fragile octets includes Turkey from the developed countries' stock markets. They used the Kanas approach (1998) to analyze the asymmetric volatility contagion effects. Findings show that fragile octets have a leverage effect for stock markets, except for the American, Asian, and European stock markets and Indonesia. Moreover, according to the findings, volatility spillovers from the stock markets of developed countries to the stock markets of the fragile octets.

In another study, applying the Kanas approach via the EGARCH model, examine the effects of average and volatility spillover from oil prices and dollar exchange to the ISE100 index for 2012-2017 and compared the effect size in terms of oil prices and dollar rate. When the results of the study are evaluated in terms of volatility spillover, a significant positive effect was observed from the dollar exchange rate to the ISE100 index, while no statistically significant effect was found from the oil prices to the ISE100 index. Additionally, it can be stated that negative shocks are more effective on ISE100 index volatility than positive shocks (Aktaş et al., 2018).

Again, in the study of Çiçek (2010), the price and volatility diffusion effects between government domestic debt securities, foreign exchange, and stock markets in Turkey are examined based on the Multivariate EGARCH Model. According to this study, there is a significant volatility spillover and asymmetric effects from the stock and foreign exchange markets to the government securities market, but there is no significant volatility spillover from the government securities market to the other two. Yorulmaz and Ekici (2010) analyzed the volatility spillover between emerging markets Turkey, Argentina, and Brazil stock market indices using daily return data for the 2001-2008 period by applying the multivariate GARCH model. It has been determined that the Turkish stock market index has a stronger relationship with the Brazilian stock market index, and there is bidirectional volatility spread between Turkey and Brazil stock indices, and unidirectional volatility spread from Brazil to Argentina and from Argentina to Turkey.

Cevik et al (2020) examined the relationship between crude oil prices and ISE returns in Turkey, considering volatility spillovers exemplified by second-moment effects. They applied the EGARCH process to capture any leverage effects volatility of returns. The empirical results of the study indicate that crude oil prices have significant effects on stock market returns in Turkey. Moreover, there are significant spillover effects from crude oil price changes to stock market returns. Şenol (2020) investigated the volatility spillovers and volatility relations of the ISE core markets using daily data for the period from January 4, 2010, to August 28, 2019. The volatility spillovers between industry, trade, service and financial sectors were analyzed by the causality test in variance, while the inter-sectoral relationships were analyzed using the DCC GARCH method. In the study, a dynamic conditional correlation relationship was observed between the volatility spillovers from the industry, trade, and service sectors to the financial sector and the ISE core markets.

Demiralay and Bayraci (2015) applied DY methodology to analyze volatility spillovers among stock markets of Central and Eastern Europe. They obtained the volatility of the stock markets' returns using the conditional autoregressive range model which makes the study particular in the spillover studies. They found that the US subprime mortgage crisis and the ongoing eurozone crises have a significant effect on volatility contagion between markets. Akça and Öztürk (2016) examined the effect Global Financial Crisis of 2008 on the markets of the US, UK, Germany, Spain, Turkey, and Greece applying the DY approach. They found that Global Financial Crisis increased the spillover between mentioned countries as time goes by. Moreover, the results showed that volatility spillovers suddenly almost double during the crisis period. Gemici (2020) aims to examine the financial connectedness between stock exchange markets of emerging E7 countries (Brazil, Russia, India, China, Indonesia, Mexico, and Turkey). In the study using the method of DY (2009, 2012), it was revealed that the total volatility diffusion index among stock exchanges is at a low level. The period in which the financial risk transition between stock exchanges is the highest has been determined as the COVID-19 pandemic period. Kamışlı and Esen (2019) analyzed the financial connectedness between the credit default swaps of Argentina, Belgium, China, Denmark, Norway, Poland and Turkey using the method developed by DY (2012) and it was determined that there is a certain level of financial connectivity between the country's credit default swaps. The total spillover index was found to be 58.51%. Mensi et al (2021) examined the dynamic asymmetric volatility connectedness among ten U.S. stock sectors (Consumer Goods, Consumer Services, Financials, Health Care, Materials, Oil and Gas, Technology, Telecom, Real Estate Investment Trust (REIT), and Utilities). They used the methodology of the DY approach. They found evidence of time-varying spillovers among U.S. stock sectors which are intensified during economic, energy, and geopolitical events. As a result, Financials, Materials, Oil and Gas, REIT, Technology, Telecom, and Utilities are the net receivers of spillover under good volatility. In contrast, Oil and Gas shift to the net contributor of spillover under bad volatility. Arı (2021) examined the volatility spillover between precious metals gold and silver in his study. In this study, Engle-Granger cointegration analysis was used methodologically similar to the DY approach. The volatilities of the variables were found using GARCH-type models. Then, the two-way volatility spillover between gold and silver was determined using both the Engle-Granger approach and the Kanas approach.

In conclusion, it is understood that there are studies on volatility spillover with different approaches in the literature. It is obvious that most of these studies examine the propagation between financial markets. The DY approach is widely used because of both the simplicity of the underlying methodology and the possibility of making a lot of inferences. The stock-based volatility spillover is an under-studied issue using DY method, at least for the Turkish markets. Therefore, only studies with methodologically similar approaches are briefly mentioned.

II. METHODOLOGY

II.I. Exponentially Weighted Moving Average Model for Volatility

The Exponential Weighted Moving Average (EWMA) is one of the most popular volatility models that relate time and volatility to calculate future volatility with the average movement of past volatility. This model is based on the principle that asset returns are distributed symmetrically and independently, and the volatility assumption that changes depending on time. This method is mostly used in risk management calculations. Its calculation is made by taking the square root of the data. The model has two basic parameters; It moves from the time and lambda values. The lambda coefficient used in the model is known as the "constant correction" or the "smoothing constant". This coefficient takes a value between 0 and 1.

From this point on, Tsay's (2012) approach will be followed to define the model. According to a prespecified theta value that determines the weights, the EWMA sample is obtained as follows.

$$\hat{x}_{n+1} = \frac{x_n + \theta x_{n-1} + \theta^2 x_{n-2} + \cdots + \theta^{n-1} x_{n-1}}{1 + \theta + \theta^2 + \cdots + \theta^{n-1}} \tag{1}$$

where $0 < \theta < 1$. This formula shows that in the prediction of the (n + 1) th term, the weight of the last days has increased and the weight coefficients decrease exponentially. This method is a common method used for point prediction of $\hat{x}_{n+1}$. Using the Maclaurin series expansion $1+\theta+\theta^2+\cdots+\theta^{n-1}=(1-\theta^n)/(1-\theta)$, then the formula can be rewritten as follows

$$\hat{x}_{n+1}=\frac{(1-\theta)\sum_{i=0}^{n-1}\theta^i x_{n-i}}{1-\theta^n}$$

For a large n, $\theta^n \rightarrow 0$ and so,

$$\hat{x}_{n+1}=(1-\theta)\sum_{i=0}^{n-1}\theta^i x_{n-i} \tag{2}$$

This point prediction can be effectively predicted because

$$\hat{x}_{n+1}=(1-\theta)\sum_{i=0}^{\infty}\theta^i x_{n-i}=(1-\theta)x_n+(1-\theta)\sum_{i=1}^{\infty}\theta^i x_{n-i}$$

$$=(1-\theta)x_n+\theta(1-\theta)\sum_{i=0}^{\infty}\theta^i x_{n-1-i}=(1-\theta)x_n+\theta\hat{x}_n$$

With an initial value such as$\hat{x}_1$, an estimate of $\hat{x}_{n+1}$ can be calculated. The first term of the formula indicates the contribution of the last observation to $\hat{x}_{n+1}$, while the second term indicates persistence in prediction. Larger θ means higher persistence and less weight for the latest data. Smaller θ means more weight and less persistence for the final data. In practice, the range for θ is approximately between 0.75 and 0.98. Also, θ can be estimated by statistical methods. As a result, the model makes its estimates by including the coefficient of recent changes and an average weight of previous estimates. Based on the study (Hull, 2000), the EWMA model

$$\hat{\sigma}_n^2=(1-\theta)u_{n-1}^2+\theta\sigma_{n-1}^2 \tag{3}$$

In the model, σ_n is calculated from volatility σ_{n-1} for n days, and $u_{n-1}$is the last change in the market. When making calculations, when a new market observation is received or when there is variability, a new u_{n-1}^2 should be calculated and used in variance estimation since the old variance rate or the old market return variability will lose its meaning.

II.II. Diebold-Yilmaz Approach for Volatility Spillover Effect

In this study, the method proposed by DY (2009, 2012) is used in estimating the directional measure of volatility propagation. DY (2009) analyzed the return volatility of the aforementioned method, assets within and between countries, asset portfolios and asset markets, etc. of propagation tendencies, cycles, bursts, etc. (DY,2009,) and developed the Diebold - Yılmaz Volatility Connectedness Index, which they applied to the daily stock return volatility of 45 countries from January 1, 2004, until the last observation phase. This index is also calculated for foreign exchange markets, government bond markets, and CDS markets.

DY(2009) describe the return and volatility spillover on the basis of the Vector Autoregressive (VAR) model. The total spillover index is measured based on the Cholesky decomposition. But, in the later study of DY(2012, 2014), they developed a methodology to evaluate directional spillover in a generalized VAR framework. This VAR framework approach offers variance decomposition that is invariant to the ordering of variables after that of Koop et al. (1996) and Pesaran and Shin (1998). In the N-component standard VAR model, each entity xi with = 1,…, N is expressed as follows:

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{4}$$

where y_t is $Nx1$ matrix of dependent variables and φ_i are NxN matrix of coefficients. ε_t is the vector of independently and identically distributed innovations (iid) and follows $\varepsilon_t \sim N(0, \Sigma)$ where Σ is variance-covariance matrix. The moving average representation of the VAR model is as follows:

$$y_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i} \tag{5}$$

where A_i are NxN matrix of moving average coefficients and $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \cdots + \varphi_p A_{i-p}$. Then, given the VAR framework, H-step-forecast error-variance decompositions are defined as follows

$$\theta_{ij}^{g} = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} \left(\Delta_i^T A_h \Sigma \Delta_j\right)^2}{\sum_{h=0}^{H-1} \left(\Delta_i^T A_h \Sigma A_h^T \Delta_i\right)} \tag{6}$$

where σ_{ij} represents the standard deviation of the error term, Σ is variance-covariance matrix and Δ_i is the selection vector of which ith element is equal to 1 and the other elements are 0. If each element of the decomposition matrix is divided by row sums, each forecasting error decomposition variance is normalized, thus using the available information in the decomposition matrix to compute the spillover effects as follows.

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

With

$$\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1 \text{ and } \sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N.$$

In the light of the above definitions and equations from 4 to 7, DY (2012) defined total, directional and net spillovers as follows.

The total volatility spillovers index based on h-step-ahead forecasts with the following equation:

$$TS^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} x100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} x100 \tag{8}$$

Directional volatility spillovers to i market from other j markets:

$$DS_{j \to i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} x100 \tag{9}$$

Directional volatility spillovers from market i to other j markets:

$$DS_{i \to j}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} x100 \tag{10}$$

The net spillover index is obtained using Equations 4.9 and 4.10 as follows

$$NS_{i}^{g}(H) = DS_{i \to j}^{g}(H) - DS_{j \to i}^{g}(H) \tag{11}$$

Average spillover effects over the full sampling period are obtained by generalized spillover analysis. DY (2009, 2012, 2014) stated that full sample spillover measurements cannot clearly reflect the important sustained and cyclical movement in spillovers. A rolling window framework was created that allows time-varying spillover indices to overcome its current shortcomings in the spillover index, using a subsample.

III. DATA AND EMPIRICAL RESULTS

The data set is divided into two periods according to the date of the first cases seen in Turkey. While the first period consisted of 267 observations between January 2, 2019, and February 28, 2020, the second period consisting of 267 observations was created between March 2, 2020, and April 1, 2021. The first period is called pre-Covid-19, while the second period is called the Covid-19 period in the study. The dataset is downloaded using "quantmod" package of R software (Ryan and Ulrich, 2020). DY analysis was performed using "Spillover" R package developed by Urbina (2020). Time series plots of the returns for both the pre-Covid-19 and the Covid-19 periods are given in Figure 1 and Figure 2.

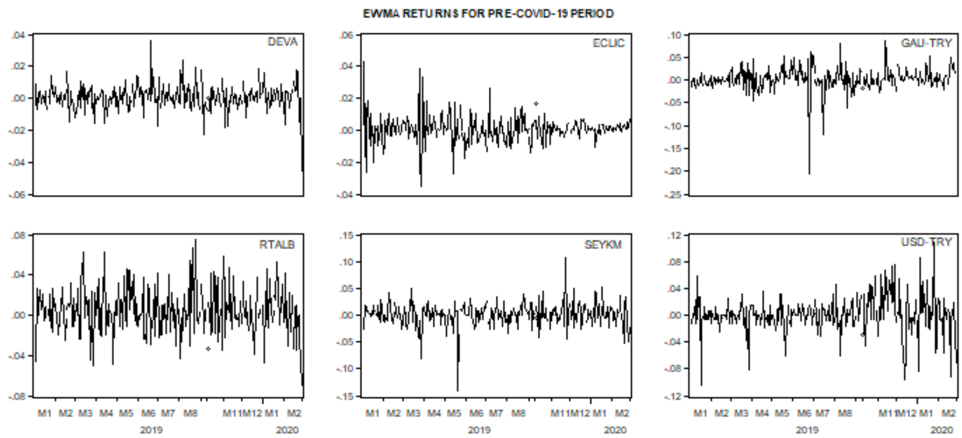

Figure 1. Time Series Plot of Returns for Pre-Covid-19 Period

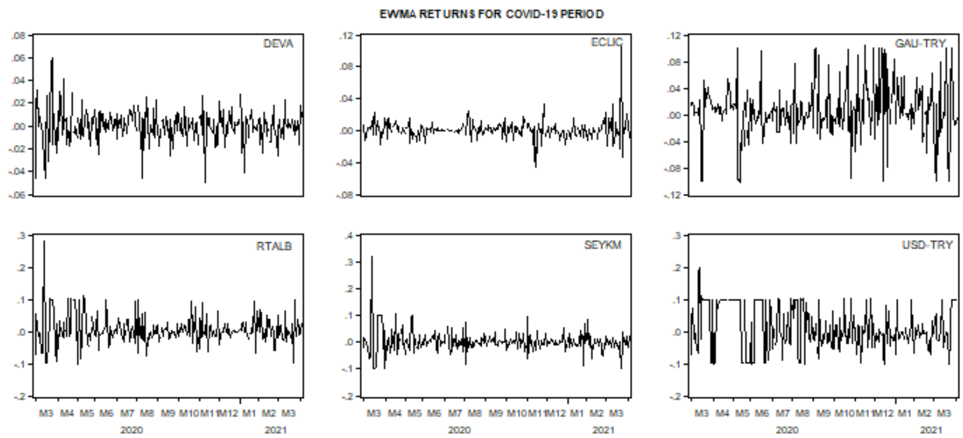

Figure 2. Time Series Plot of Returns for Covid-19 Period

III.II. Findings

Descriptive statistics of the volatility data obtained from EWMA models for both periods are given in Appendix A in Table A1 and Table A3, respectively. Correlation values between volatilities are also given in Appendix A in Table A2 and Table A4, respectively. Time series graphs of the volatility series obtained using the EWMA model for the both periods are presented in Figure 3 and Figure 4.

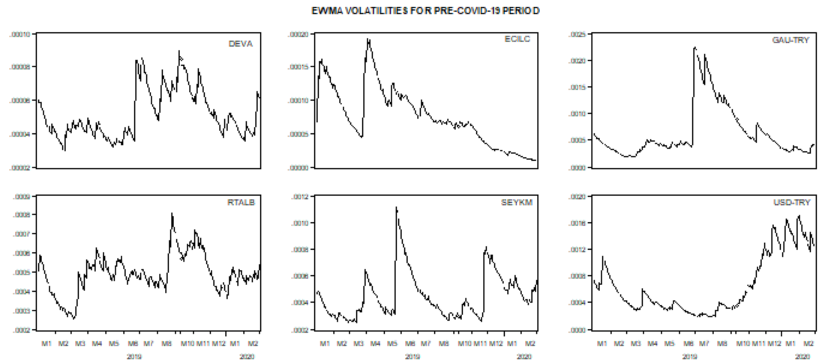

Figure 3. Time Series Plot of EWMA Volatilities for Pre-Covid-19 Period

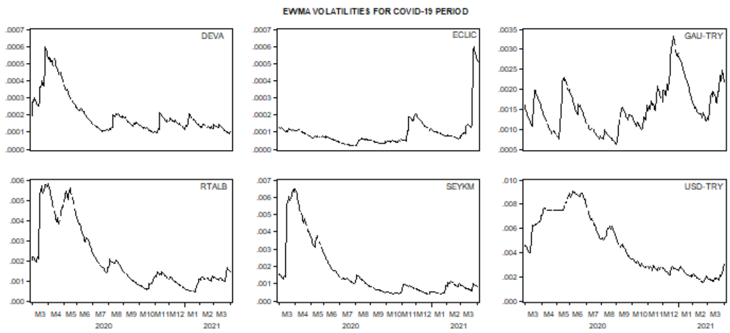

Figure 4. Time Series Plot of EWMA Volatilities for Covid-19 Period

In the pre-Covid-19 period, the high positive correlation between DEVA volatility and GAU-TRY and RTALB volatility and the negative correlation between USD-TRY and ECILC volatility are remarkable. In addition, the correlation between SEYKM and USD-TRY and GAU-TRY volatilities are in a different direction with the correlation between these exchange rate volatilities and other stock volatilities. In the Covid-19 period, the correlation between DEVA and RTALB and SEYKM volatilities has a very high positive value, while the ECILC volatility has a positive correlation only with GAU-TRY.

When we look at the total spillover index in the period before Covid-19 given in Table 1, it is seen that it was 9.60%, and this result indicates a low connectedness between markets. In other words, on average, the volatility shocks related to other markets account for 9.60% of the volatility forecast error variance in our sample. According to the net volatility spillover values, DEVA, ECILC, and RTALB are volatility transmitters in this period, while exchange rates and SEYKM are volatility receivers.

Looking at the CfO values which have a range between 1.50% and 24.80% for ECILC and GAU-TRY, respectively. It may be concluded that volatility in all observed assets is at least 1.50% caused by the events taking place in other markets. GAU-TRY, which is included in the study as a representative of precious metals, is the most affected by the shocks in other markets. These results are consistent with the economic theory since precious metals are often used as a hedging instrument against when adverse events occur in other markets.

Table 1. NY Volatility Spillover Index for Pre-Covid-19 Period

	DEVA	ECILC	GAU	RTALB	SEYKM	USD	CfO
DEVA	92.20	3.00	0.60	2.00	0.30	1.80	7.80
ECILC	0.10	98.50	0.30	0.40	0.00	0.70	1.50
GAU	19.00	0.30	75.20	1.10	2.90	1.50	24.80
RTALB	0.20	0.80	0.10	96.20	1.70	1.00	3.80
SEYKM	3.10	0.30	0.00	7.20	89.40	0.00	10.60
USD	0.10	0.30	0.40	3.30	4.70	91.20	8.80
CtO	22.50	4.70	1.40	14.00	9.60	5.10	57.30
CiO	114.70	103.20	76.60	110.20	98.90	96.30	9.60%
NS	14.70	3.20	-23.40	10.20	-1.10	-3.70	

CtO: Contribution to Others. **CiO:** Contribution including Own. **CfO:** Contribution from Others. **NS**: Net Spillover.

In this study, a rolling window framework was created that allows time-varying spillover indices to overcome its current shortcomings in the spillover index, using a 20-day subsample. The forecasting spillover for the pre-COvid-19 period is represented in Figure 3.

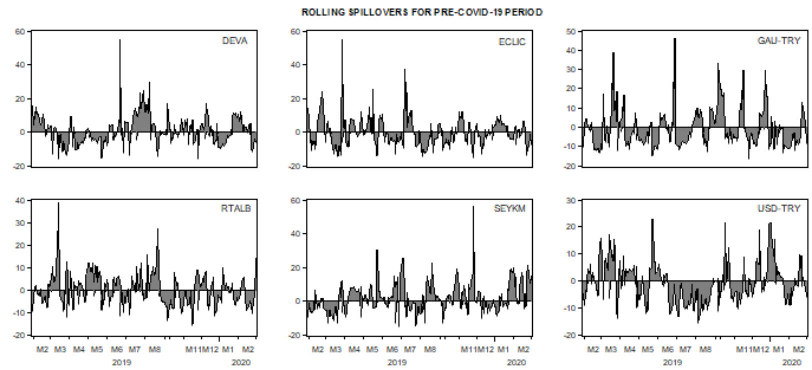

Figure 5. Rolling Volatility Spillovers for Pre-Covid-19 Period

The spillover index for the Covid-19 period is in Table 2. In the Covid-19 period, the increase in the index value to 21.90% shows that the connectivity between the markets has increased and the error variance in stocks and exchange rates is on average 21.90% originated from other markets. It is noteworthy that 82.80% of the current error variance in SEYKM volatility originates from RTALB. The impact of shocks arising from the vaccine study news increased the persistence of RTALB volatility and had a spillover effect of 71.90% during the Covid-19 period.

Table 2. NY Volatility Spillover Index for Covid-19 Period

	DEVA	ECILC	GAU	RTALB	SEYKM	USD	CfO
DEVA	89.80	0.00	0.10	7.60	0.30	2.20	10.20
ECILC	0.20	99.30	0.30	0.00	0.10	0.00	0.70
GAU	0.00	3.30	94.40	1.30	0.20	0.80	5.60
RTALB	1.00	2.10	0.80	83.70	0.40	11.90	16.30
SEYKM	1.80	0.80	0.70	70.20	15.20	11.30	84.80
USD	0.80	2.10	0.80	9.00	1.20	85.90	14.10
CtO	3.90	8.40	2.70	88.20	2.20	26.20	131.60
CiO	93.70	107.70	97.10	171.90	17.40	112.20	21.90%
NS	-6.30	7.70	-2.90	71.90	-82.60	12.20	

CtO: Contribution to Others. **CiO:** Contribution including Own. **CfO:** Contribution from Others. **NS:** Net Spillover.

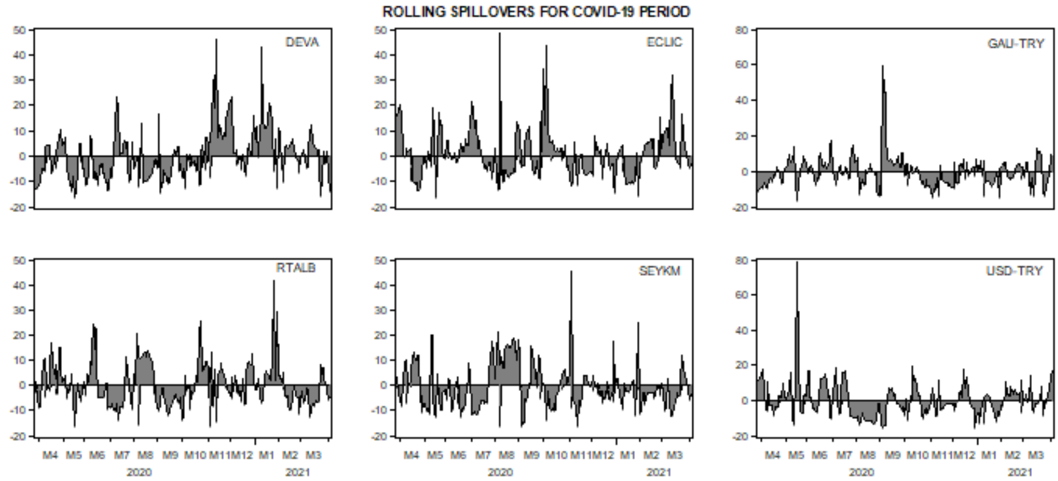

Figure 6. Rolling Volatility Spillovers for Covid-19 Period

Looking at the Covid-19 period rolling spillover windows, the first thing that strikes the eye is the net spillover value of RTALB stock in January 2021. This situation can be understood from the Public Disclosure Platform (PDP) notifications. The extreme volatility that started on January 26, 2021, continued on January 28, 2021. During this period, orders received by the company increased the fluctuations in the stock price, which started before. As a result of this circuit breaker has been activated in the related instrument (PDP, 2021).

CONCLUSION

The volatility in financial markets is not only influenced by local markets, but also by international markets. This effect originating from international markets is more effective in developing country markets. However, the financial crisis experienced in any local market affects all financial markets. The role of rapid access to information in the formation of this effect is very important (Gemici, 2020). The speed in accessing information can increase volatility in financial markets, as well as reduce volatility persistence. In this case, the question arises which financial asset volatility affects other volatilities. The answer to this question is found in volatility spill analysis. Therefore, volatility studies have become important for market players and policymakers. Volatility spillovers can be measured by different methods and provide a significant improvement in the econometrics literature as well as in the finance literature. In this study, it is important to obtain the volatility data for the Diebold-Yılmaz approach via the EWMA model.

In this context, according to the results of the study, the connection between gram gold, dollar, and health sector stocks increased and reached 21.90% in the Covid-19 period. According to the net volatility spillovers, the ECILC, RTALB, and USD-TRY exchange rate should be carefully monitored by investors during this period. Especially the high volatility in RTALB creates an opportunity and it is seen that keeping it in the same basket with SEYKM stock in portfolio diversification will increase the risk. It is concluded that the net volatility spillover from RTALB stock to SEYKM stock is 69.80% where total spillover from RTALB to SEYKM is 70.20%, vice versa 0.40%.

The lack of a health sector index in the Istanbul Stock Exchange can be cited as the biggest limitation of the study. The stock returns and volatility of companies operating in the health sector with all their branches are included in the study. During the Covid-19 period, companies that were newly listed on the stock market and companies whose main branch was not health, but also operating in the health sector were not included in the study. In addition, the fact that ISE was a fluctuating and risky stock market in the pre-pandemic period should also be taken into account, which prevents the effect of the Covid-19 period from being clearly identified.

At the same time, it should not be forgotten that cryptocurrency markets attract attention during the pandemic period as an alternative to Turkish markets for domestic investors. Cryptocurrency markets have created an important alternative for Turkish investors to both foreign exchange, precious metals, and stock markets. It is important that cryptocurrency market assets are also included in future studies on volatility spillover and financial connectedness. With this state of the study, it is understood that health sector assets are an important tool for investors in Turkish markets as in the whole world.

In conclusion, the findings of such studies are important for investors, market regulators, and policy makers. Particularly, volatility spillover studies constitute a reference for risk perception and portfolio diversification.

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Appendix A

Table A1. Descriptive Statistics of EWMA Volatilities for Pre-Covid-19 Period

	DEVA	ECILC	GAU	RTALB	SEYKM	USD
Mean	0.0001	0.0001	0.0006	0.0005	0.0004	0.0007
Median	0.0000	0.0001	0.0004	0.0005	0.0004	0.0004
Maximum	0.0001	0.0002	0.0022	0.0008	0.0011	0.0017
Minimum	0.0000	0.0000	0.0002	0.0003	0.0003	0.0002
Std. Dev.	0.0000	0.0000	0.0005	0.0001	0.0002	0.0004
Skewness	0.7617	0.4734	1.7341	0.1117	1.4191	0.8769
Kurtosis	2.4793	2.6085	5.1067	3.2974	5.0528	2.3601
Sum	0.0138	0.0200	0.1696	0.1308	0.1200	0.1758
Sum Sq. Dev.	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001

Table A2. Correlations Between EWMA Volatilities for Pre-Covid-19 Period

	DEVA	ECILC	GAU	RTALB	SEYKM	USD
DEVA	1.0000	-0.1858	0.6493	0.4485	-0.2120	-0.2371
ECILC	-0.1858	1.0000	0.0075	0.0522	-0.0146	-0.5666
GAU	0.6493	0.0075	1.0000	0.2130	-0.0928	-0.4218
RTALB	0.4485	0.0522	0.2130	1.0000	0.0661	-0.1216
SEYKM	-0.2120	-0.0146	-0.0928	0.0661	1.0000	0.2208
USD	-0.2371	-0.5666	-0.4218	-0.1216	0.2208	1.0000

Table A3. Descriptive Statistics of EWMA Volatilities for Covid-19 Period

	DEVA	ECILC	GAU	RTALB	SEYKM	USD
Mean	0.0002	0.0001	0.0015	0.0021	0.0016	0.0046
Median	0.0002	0.0001	0.0015	0.0014	0.0009	0.0041
Maximum	0.0006	0.0006	0.0033	0.0058	0.0065	0.0091
Minimum	0.0001	0.0000	0.0006	0.0005	0.0004	0.0015
Std. Dev.	0.0001	0.0001	0.0006	0.0016	0.0016	0.0024
Skewness	1.6834	3.9096	0.7926	1.1288	1.7106	0.3975
Kurtosis	4.9792	20.2332	3.4033	2.8664	4.7732	1.6934
Sum	0.0539	0.0254	0.4096	0.5574	0.4346	1.2290
Sum Sq. Dev.	0.0000	0.0000	0.0001	0.0007	0.0007	0.0015

Table A4. Correlations Between EWMA Volatilities for Covid-19 Period

	DEVA	ECILC	GAU	RTALB	SEYKM	USD
DEVA	1.0000	-0.0291	-0.1303	0.8446	0.9190	0.5673
ECILC	-0.0291	1.0000	0.4582	-0.0475	-0.0219	-0.2810
GAU	-0.1303	0.4582	1.0000	-0.1607	-0.1447	-0.3552
RTALB	0.8446	-0.0475	-0.1607	1.0000	0.9401	0.7914
SEYKM	0.9190	-0.0219	-0.1447	0.9401	1.0000	0.6496
USD	0.5673	-0.2810	-0.3552	0.7914	0.6496	1.0000

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