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The CARR-volatility connectedness between USD/TRY and foreign banks in Turkey: Evidence by TVP-VAR

This study focuses on the volatility spillover between the stock prices of foreign banks having business in Turkey and the exchange rate. More particularly, it analyzes the connectedness between the USD-TRY exchange rate volatility and the foreign banks' stock price volatility in their own country's stock markets. We select ten foreign banks with the biggest total assets and divide them into two panels: eastern and western capitalized banks. The dataset contains weekly data from 2016-01-04 to 2022-01-17. We estimate volatilities utilizing the Conditional Autoregressive Range (CARR) model and then apply the Time-Varying Parameter-Vector Autoregressive (TVP-VAR) based Diebold–Yilmaz Connectedness Index to reveal the transition and connectedness of volatility. The total connectedness indices show that 26.72 and 54.75% of the forecast error variance originate from other assets included in the spillover analysis for eastern and western panels, respectively. We also explore net pairwise co-movements and find that shocks in USD-TRY have dominated on the forecast error variance of bank stocks in the eastern panel, while it is a net volatility receiver in the western panel.

Keywords: Diebold–Yilmaz Connectedness Index; dynamic connectedness; CARR; TVP-VAR.
JEL classification: C11; C53; C58; F31; G15.

1. Introduction

Stock markets are often a critical indicator of the financial and economic market and trends in stock prices can be considered a sign of economic contraction or growth. The returns and risks of other financial instruments and the monetary policy decisions affect the risk of stock markets. Although stock markets and exchange rates offer alternative investment opportunities to investors, the return and risk relationship between the two markets has a dynamic structure. Banks act as a bridge between these two markets and the relationship between the stock returns of banks and the change in exchange rates may create a complex structure. Merton's Intertemporal Capital Asset Pricing Model (1973) and French et al.'s (1983) Nominal Contract Hypothesis are approaches based on the relationship between bank stock returns and interest/exchange rate changes. Today, the developments in econometric approaches provide better implications for explaining this relationship. Before moving on to these approaches, it is useful to examine the elements underlying the theory of Kasman et al.'s (2011) study. They explain that the nominal assets and nominal liabilities held by a bank affect stock returns through wealth distribution effects caused

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by unanticipated inflation. This situation differs due to banks not completing their internationalization processes and divergences in retail/commercial banking practices. In other words, the exchange rate sensitivity of each bank is heterogeneous. It is an accepted fact that monetary policy and changes in exchange rates directly affect the income and profitability of banks (Borio et al., 2017). Therefore, we can list the maturity mismatch between banks' assets and liabilities as well as unexpected changes in exchange rates as factors affecting the equilibrium price of bank stocks. Banks can reduce exchange rate risk by applying risk management techniques, however international banks must consider various kinds of market risks. Especially banks with foreign capital established in developing countries may become more fragile due to the inadequacy of such tools and techniques in the countries where they are located. Banks with foreign capital must manage the current exchange rate risk both in the countries in which they operate and in their home countries. Studies by Shamsuddin (2009) for Australian banks and Kasman et al. (2011) for Turkish banks conclude that both the change in interest and exchange rates has a negative effect on bank stock return. Moreover, Kasman et al. (2011) find that the main factors of volatility in bank stocks in Turkey are interest/exchange rate volatilities

In these mentioned studies, researchers mostly utilize multivariate GARCH models, and make inferences about return and volatility spillovers based on the correlation analysis. Correlation measures the direction and strength of linear dependence between two variables. However, non-linear characteristics of financial time series can be captured by moving to a conditional perspective with time-varying correlations. Engle's (2009) dynamic conditional correlation GARCH model and dynamic equicorrelation approach of Engle, Kelly (2012), which are widely used in the analysis, are assumed as an example. Since the correlation function is symmetric, the correlation is also undirected and is only a bilateral measure of the relationship. Often, researchers wish to go beyond binary interconnections by exploring the connectedness of entire markets in a directionless way. Therefore, the methodology of this study is based on Diebold and Yilmaz's (2009) approach, as it allows asymmetries in bilateral connections between markets, instead of inherently symmetrical (hence non-directional) measures such as correlation. Diebold and Yilmaz propose the connectedness index to estimate the directional measure of volatility spillover. The Diebold–Yilmaz Connectivity Index (DYCI) provides the opportunity to decompose the impact of shocks from other financial assets within the estimation error variance of each financial asset. Diebold and Yilmaz states that the method in question can be used to measure the spread trends, cycles, and bursts of the return volatility of assets, asset portfolios, and asset markets both within and between countries. Furthermore, connectedness measurement is potentially useful in crisis monitoring, as connectedness tends to increase sharply during crises.

Diebold and Yilmaz's (2009, 2012, 2014) VAR-based interconnectedness approach has received considerable attention from the currently available economic and financial literature and has also been applied to issues related to stock market interdependencies, volatility spillovers, business cycle spillovers. The Diebold–Yilmaz approach facilitates the measurement of interdependence over a network of variables. Thus, it should be noted that it provides a framework for analyzing both a unique effect and the effect made by others. The following measures are based on the estimation of the estimation error variance decompositions derived from a VAR model. In addition, this method yields results for total, directional, and net interdependence. These results allow us to further classify interdependence and provide detailed information. More specifically, in the case of net interdependence, this measure allows distinguishing between net shock transmitter and net shock receivers, which helps to better understand the underlying dynamics and facilitates the formulation of policy outcomes. Diebold, Yilmaz (2009) use a VAR framework with Cholesky decomposition. Although the Diebold–Yilmaz's model (2009) has been used in many studies, it 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 where the ordering of variables is irrelevant.

Finally, Diebold and Yilmaz (2014) emphasize the concept of connectivity and enables a more accurate determination of potential changes in parameter values. With this approach, where outliers do not affect the results, there is no need to set arbitrary rolling window size. Thus, there is no loss of observation in the calculation of dynamic measures. 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 and Gabauer (2017) develop a connectedness model based on the time-varying parameter vector autoregression (TVP-VAR) model. Another groundbreaking study is (Korobilis, Yilmaz, 2018).

Both studies adopt a similar framework, although they examine the connectedness between two different financial markets, such as the exchange rate market and the European-American stock markets, respectively. As a result of both studies, it was determined that the TVP-VAR-based connectedness model immediately adapts to the events, while the original model based on the rolling windows either overreacts to the events or softens the effect. The TVP-VAR model, with its stated advantages, overcomes the burden of the often arbitrarily chosen rolling window size, which can lead to very irregular or flattened parameters and loss of valuable observations. Later, Antonakakis et al. (2020) propose a method for constructing confidence intervals of dynamic connectedness by combining 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. Antonakakis et al. (2020) further strengthen the argument in favor of connectedness measures established by TVP-VAR.

This study adapts the connectedness approach proposed by Antonakakis et al. (2020) which is based on (Diebold, Yilmaz, 2012, 2014). As a result, this study uses the TVP-VAR model, which is expanded by allowing variance-covariance variation through a Kalman filter estimation accompanied by Koop and Korobilis (2013, 2014) forgetting factors.

Volatility is expressed as a measure of the possible deviation of the price of any asset from its average value at a given time. According to (Craighead, 2009), exchange rates have high volatility compared to other variables of the economy. First of all, excessive fluctuations in exchange rates damage the confidence of economic decision-makers in the market and prevent them from making the right decisions. Once the market reaches high volatility, the gap between expectation and reality becomes even greater. Another effect of high volatility is on firms and firm stock prices. Sudden decreases and increases in exchange rates cause uncertainty and a lack of confidence in companies. On the other hand, volatility in exchange rates may directly lead to significant negative effects on foreign investments due to the uncertainties they cause.

This study focuses on foreign banks operating in Turkey in order to understand the risks created by high exchange rate volatility in Turkey. We may present some of the studies including volatility spillover between exchange rates and banks' stock prices in the literature as follows. Priti (2016) investigates the volatility spillovers interest rates, exchange rates and portfolios of money centres, large and medium-sized banks in the U.S. using the multivariate Exponential GARCH model. He finds significant volatility spillover between short-term and long-term interest rates and exchange rates to all the three bank portfolios. Mouna and Anis (2016) test the causal relationships between the variables the financial stock return, the exchange rate, the interest rate, and the stock return. They apply four-variate GARCH-in-mean model to explore the four-variate GARCH-in-mean model between mentioned variables. The researchers focus on three financial sector returns financial, insurance, and banking sector in eight countries namely Germany, USA, Greece, UK, France, Spain, Italy, and China. They find there is a positive and negative effect of the exchange rate volatility, the short-term interest rate, and the stock market returns on the banking sector in the majority of cases. In addition, they observe a significant positive effect in a few cases from the exchange rate volatility and the stock market to the insurance sector.

Although Ong and Cihak (2007) did not consider the effect of the exchange rate, they examined the scope for cross-border spillovers among the major European banks using the Extreme Value Theory framework. Their data sample comprises the 33 largest listed EU banks which have about half of the total EU banking system assets. They find that the spillover risks are spread far from evenly across the large EU banks and some of the banks like the Bank of Ireland have no significant spillover impact on other banks. In addition, they indicate that Fortis is the bank with the biggest potential for spillover while HSBC is second. Elyasiani et al. (2015) examine the return and volatility interdependencies among USA, UK, EU, and Japanese banks and insurers using the multivariate GARCH model. They find significant volatility transmissions among banking and insurance industries. Also, they indicate that contagious spillover effects become robust during the crisis of 2007 to 2009, and a leading role played by the US financial institutions as information providers in global markets. Chen et al. (2022) apply the Student-T GARCH model to obtain the volatility of the banking market and internet financial market volatility in China. They use the Diebold–Yilmaz volatility spillover index approach to analyse the interconnectedness between banking and internet financial markets while the residual data and the estimated conditional variance are based on the wavelet multi-resolution analysis method of the maximal overlap discrete wavelet transform. Thus, the decomposition of the residual information and volatility information into different time periods can be analysed.

Another notable study is (Arbaa, Varon, 2019). They examine the impact of a Turkish Lira crisis on August 10, 2018, on the stock prices of the largest European banks. They apply the Fama–French five-factor asset pricing model to determine the abnormal returns in the event window using the 21 European and Turkish banks' data. Their findings show that the most affected bank are Turkish banks. Also, they provide evidence that Greece, Netherlands, Italy, Spain, Germany and France show significant cumulative abnormal losses while banks of the UK and Switzerland have no significance in the returns. Moreover, interestingly, they find that Dutch banks have much larger cumulative abnormal losses than Italian and Spanish Banks, despite having a much lower exposure to Turkey. They conclude that the largest economies in the EU such as Germany, Netherlands and France do not seem immune to the possible spillover effects of a financial crisis in Turkey.

Another important study with a methodology similar to the approach of this study is (Demiralay, Bayraci, 2015). The authors reveal the volatility pass-through between the Central and Eastern European stock markets using the Diebold–Yilmaz approach. They estimate the volatility of stock index returns with the Conditional Autoregressive Range (CARR) model. The Diebold–Yilmaz spillover index used in the study is based on the generalized VAR model. Therefore, we may indicate that estimating exchange rate volatility and foreign bank stock return volatility using CARR-type models is not a common approach. Although the TVP-VAR approach is a popular method in recent years, it is still very new, this approach has not been applied to determine the spillover index of foreign exchange rate and banks' stocks. We expect this study to lead to literature that includes the CARR-volatility Diebold–Yilmaz connectedness between the USD/TRY exchange rate and bank stock prices. For this purpose, it aims to analyze the connectedness between the USD-TRY exchange rate volatility and the foreign banks' stock price volatility in their own country stock markets. We choose ten foreign banks with the highest asset size and divide them into two groups as eastern and western capitalized banks. Bank stock price volatility and exchange rate volatility are estimated with the CARR model. Then we use the TVP-VAR based Diebold–Yilmaz Connectedness Index (DYCI) to reveal the transition and connectedness between the volatilities.

The content of the study consists of five parts following the introduction. The second and third parts of the study includes the empirical methodology. These sections cover the CARR model and TVP-VAR based DYCI, respectively. The study continuous with the fourth and the fifth sections that present the dataset and empirical findings of volatility model and connectedness approach, respectively. The paper ends with the conclusion part.

2. Conditional autoregressive range model for volatility

The range, which is a well-known variability measure in statistics, is one of the good estimates of the standard deviation of a random variable. The range value of the distribution of any random variable is proportional to the standard deviation. Parkinson (1980) introduces the first range-based volatility approach. He measures daily volatility utilizing the daily range of the high/low prices and shows that the use of extreme values provides a better estimate.

Engle (1982) introduced the Autoregressive Conditional Heteroskedastic (ARCH) model in his study using UK inflation data. Bollerslev (1986) developed the Generalized ARCH (GARCH) model, in which the conditional variance in the instantaneous period depends not only on the historical values of the error terms, but also on the conditional variances in the past. Thus, many versions of GARCH-type models have taken their place in the literature, which eliminates the inability of the ARCH model to capture some stylized facts of financial time series. Later, Chou (2005, 2006) that used the idea of GARCH models to examine the dynamic nature of the range introduced the Conditional Autoregressive Range (CARR) model to the literature. Since the range is necessarily non-negative, CARR models are also applied to model time series of positive observations. It is a simple and effective model for analyzing volatility clusters. Moreover, it is also convenient for using many probability distributions defined in positive real space. In addition, the model is successful in estimating volatility during periods of downward trends (Quiros, Izquierdo, 2011). This study includes Exponential CARR (Chou, 2005) and Gumbel CARR (Demiralay, Bayraci, 2015) as variants of the volatility model. One can follow Ratnayake (2021) for details of CARR-type models and their new extensions. The dynamic specification of the CARR(p,q) model constructed for the range values of a time series is as follows.

$$R_t = \lambda_t z_t, \quad z_t \sim f(1,s), \ \lambda_t = \omega + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{i=1}^{q} \beta_i \lambda_{t-i}, \tag{1}$$

where R_t is the range and is obtained by $R_t = \max(P_\tau) - \min(P_\tau)$ for $\tau \in [t-1, t]$. R_t is calculated as the difference between the highest and lowest logarithms of the prices of a financial asset observed at time τ. λ_t is the conditional mean of the range up to time t. It is assumed that the distribution of the innovation term z_t is distributed by a unit-mean density function $f(\cdot)$. In addition, the coefficients in equation (1) are all positive to ensure the positivity of λ_t.

3. TVP-VAR based dynamic connectedness

Antonakakis et al. (2020) extend Diebold and Yılmaz's (2014) originally proposed connectedness approach with the TVP-VAR method by allowing the variance-covariance matrix to vary using a Kalman filter estimation with forgetting factors like in the study of Koop and Korobilis (2013, 2014). I estimate the heteroskedastic variance-covariate TVP-VAR model to explore the time-varying link between bank stock return volatility and currency volatility. Bayesian information criteria (BIC) gives the TVP-VAR(2) model as the appropriate model. The mathematical representation of the TVP-VAR(2) model is as follows

$$y_t = \mathrm{B}_t z_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t), \tag{2}$$

$$vec(\mathrm{B}_t) = vec(\mathrm{B}_{t-1}) + \upsilon_t, \quad \upsilon_t \sim N(0, \mathrm{S}_t), \tag{3}$$

where y_t and $z_{t-1} = (y_{t-1}, y_{t-2})'$ represents $m\times 1$ and $2m\times 1$ vectors, respectively, $\mathrm{B}_t = (\mathrm{B}_{1t}\ \mathrm{B}_{2t})$ is $m\times 2m$ dimensional matrix, ε_t and υ_t are $m\times 1$ and $2m^2\times 1$ dimensional vectors, respectively. Σ_t and S_t are time-varying variance-covariance matrices of which dimensions are $m\times m$ and $2m^2\times 2m^2$, respectively. Last, $vec(\mathrm{B}_t)$ is a $2m^2\times 1$ dimensional vector.

Diebold–Yilmaz approach is based on the Generalised Forecast Error Variance Decomposition (GFEVD) of (Koop et al., 1996; Pesaran and Shin, 1998). Thus, TVP-VAR needs to be transformed into TVP-VMA Wold representation that is $y_t = \mathrm{B}_{1t} y_{t-1} + \mathrm{B}_{2t} y_{t-2} + \varepsilon_t = \sum_{h=0}^{\infty} \mathrm{A}_{ht}\varepsilon_{t-h}$, where $\mathrm{A}_{0t} = I_m$ (unit $m\times m$ matrix) and A_{ht} demonstrates a $m\times m$ dimensional time-varying VMA coefficient matrix (A_{ht} is zero for $h > t$). We can calculate the pairwise directional connectedness from j to i and reveal the influence variable j has on variable i in terms of its forecast error variance share using GFEVD. So, one can model the impact a shock in series j has on series i via H-step ahead GFEVD that is formulated as follows

$$\tilde{\varphi}^g_{ij,t}(H) = \frac{\sum_{h=0}^{H-1}\left(\varepsilon_i'\, \mathrm{A}_{ht}\Sigma_t\varepsilon_j\right)^2}{\left(\varepsilon_i'\, \Sigma_t\varepsilon_j\right)\sum_{h=0}^{H-1}\left(\varepsilon_i'\, \mathrm{A}_{ht}\Sigma_t\mathrm{A}_{ht}'\varepsilon_i\right)} \tag{4}$$

with $\sum_{j=1}^{m}\tilde{\varphi}^g_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m}\tilde{\varphi}^g_{ij,t}(H) = m$. In equation (4) the denominator is the cumulative effect of all the shocks, while the numerator represents the cumulative effect of a shock in variable i. Thus, the Total Connectedness Index (TCI) of Diebold and Yilmaz (2014) via GFEVD is calculated as follows

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\varphi}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{m} \tilde{\varphi}_{ij,t}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\varphi}_{ij,t}^{g}(H)}{m} \times 100 . \quad (5)$$

One can construct how a shock in one variable spills over to other variables by TCI. In other words, we can calculate the transmission of a shock in variable *i* to all other variables, called Total Directional Connectedness to Others (TDCtO) that is defined as follows

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,j\neq i}^{m} \tilde{\varphi}_{ji,t}^{g}(H)}{\sum_{j=1}^{m} \tilde{\varphi}_{ji,t}^{g}(H)} \times 100. \quad (6)$$

Likewise, for the opposite situation, the calculation for the receiving of the shock, called Total Directional Connectedness from Others (TDCfO) is as following

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,j\neq i}^{m} \tilde{\varphi}_{ij,t}^{g}(H)}{\sum_{i=1}^{m} \tilde{\varphi}_{ij,t}^{g}(H)} \times 100 . \quad (7)$$

The Net Total Directional Connectedness (NTDC) is equal to the subtraction of TDCfO from TDCtO. NTDC shows the effect of the variable *i* on the analyzed financial or macroeconomic network. If this value is positive, it means that the variable *i* affects the network more than the network itself is affected. Conversely, if it is negative, it means that the variable *i* is driven by the analyzed network. So, NTDC is defined as

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H). \quad (8)$$

In order to understand which variable dominates the other variable, we can examine the bidirectional relationships by calculating the net pairwise directional connectedness (NPDC). For computing NPDC, we further break down the NTDC as in the following equation

$$NPDC_{ij}(H) = \left(\tilde{\varphi}_{ji,t}^{g}(H) - \tilde{\varphi}_{ij,t}^{g}(H)\right) \times 100 . \quad (9)$$

$NPDC_{ij}(H) > 0$ indicates that variable *i* dominates variable *j* while $NPDC_{ij}(H) < 0$ indicates that variable *i* dis dominated by variable *j*.

4. Data set

The data set includes USD/TRY exchange rate range and the stock range of the ten foreign capital banks operating in Turkey with the largest asset size in their own countries. The data set consists of two panels of groups, eastern and western, according to the locations of the countries to which the banks belong. Table 1 presents bank groups and data sources. Logarithmic ranges calculated on weekly data both prevent data loss and are suitable for the range-based conditional volatility model. The data are weekly frequent and cover the period from 2016-01-04 to 2022-01-17. Table A1 in Appendix A gives the descriptive statistics of log-range data. The time-series graphs of the ranges are available in Figure 1 and Figure 2.

Table 1. Bank groups and data source symbols

N	Bank in Turkey	Owner	Country	Ticker (Symbol)
		Eastern panel		
1	Alternatifbank	The Commercial Bank of Qatar	Qatar	CBQK.QA (CBQK)
2	QNB Finansbank	Qatar National Bank	Qatar	QNBK.QA (QNBK)
3	Denizbank	Emirates NBD Bank	United Arab Emirates	EMIRATESNBD.AE (NBD)
4	Burgan Bank Türkiye	Burgan Bank	Kuwait	BURG (BURG)
5	ICBC Turkey Bank	ICBC Bank	China	1398.HK (ICBC)
		Western panel		
1	Garanti BBVA	Banco Bilbao Vizcaya Argentaria	Spain	BBVA.MC (BBVA)
2	ING	Internationale Nederlanden Groep	Netherlands	INGA.AS (ING)
3	HSBC Türkiye	Hongkong and Shanghai Banking Corporation	United Kingdom	HSBA.L (HSBC)
4	Citibank	Citibank	USA	C (CITI)
5	Deutsche Bank	Deutsche Bank	Germany	DBK.DE (DBK)

*Note*s. Burgan Bank stock prices data has been downloaded from https://www.investing.com/. Other stocks' prices data have been downloaded from https://finance.yahoo.com/. The Banks Association of Turkey's website (https://www.tbb.org.tr/en/home) has a ranking of banks by total assets. Even though Bank Audi's Odeabank is one of Turkey's top ten foreign banks, it is not featured in the list. Because there are many missing observations in the Bank Audi stock price data for the time period indicated.

5. Empirical findings of CARR volatility models

Table 2 presents the CARR(1,1) model[2] outputs. The results show that the coefficient sums of both ECARR and GCARR models are less than one, providing covariance stationarity. The Kolmogorov–Smirnov (KS) test results show that the error terms fit well with the Gumbel distribution for GCARR, while the error terms of the ECARR model do not fit well with the Exponential distribution. This concludes that ECARR estimators are consistent but not sufficient. Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) indicate that the ECARR model is better than the GCARR model. Table B1 in Appendix B shows the descriptive statistics of the volatility series obtained from the ECARR and GCARR models. The skewness and the excess kurtosis statistics in Table B1 in Appendix B indicates that all volatility series are skewed to the right and have excess kurtosis with respect to the normal distribution. These results are supported by Jarque–Bera test statistics that also indicate the series are not normally distributed at the 1% significance level. Statistics $Q(10)$ and $Q^2(10)$, expressing errors and the squares of errors, show that the series contain autocorrelation. So, one can apply Elliot–Rothenberg–Stock (ERS) test to check for stationarity of the volatility series. In addition to ERS test, we utilize Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP)

[2] We utilize *R* software to estimate CARR(1,1) models with Exponential and Gumbel distributed innovations. We can share *R* codes upon request.

PANEL EAST

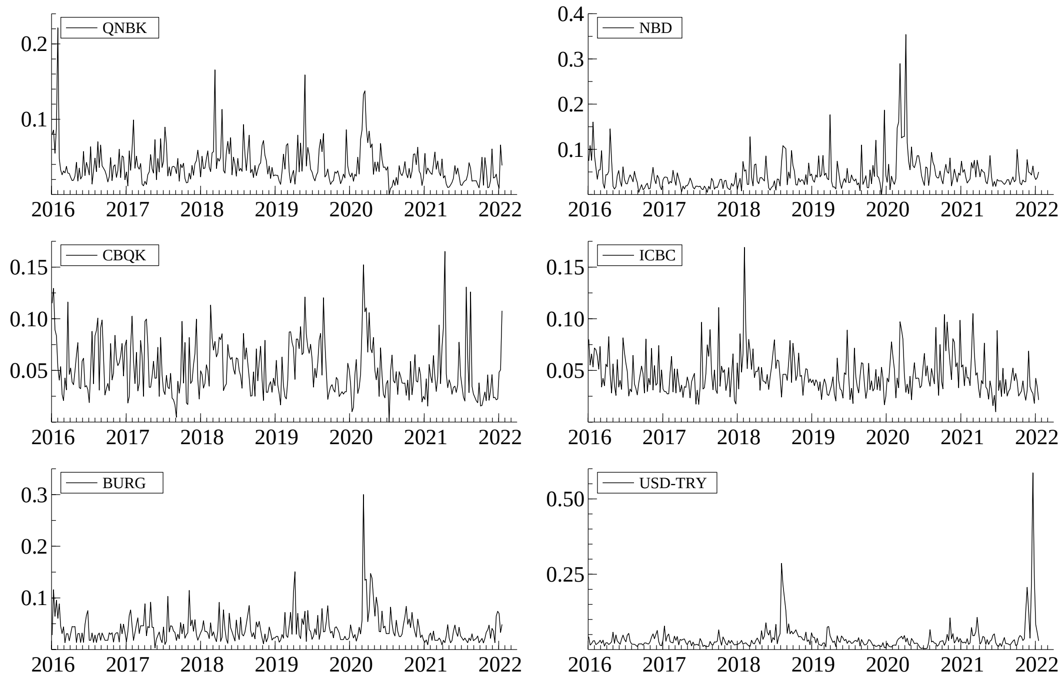

Fig. 1. Time series plots for log-range data of eastern panel

PANEL WEST

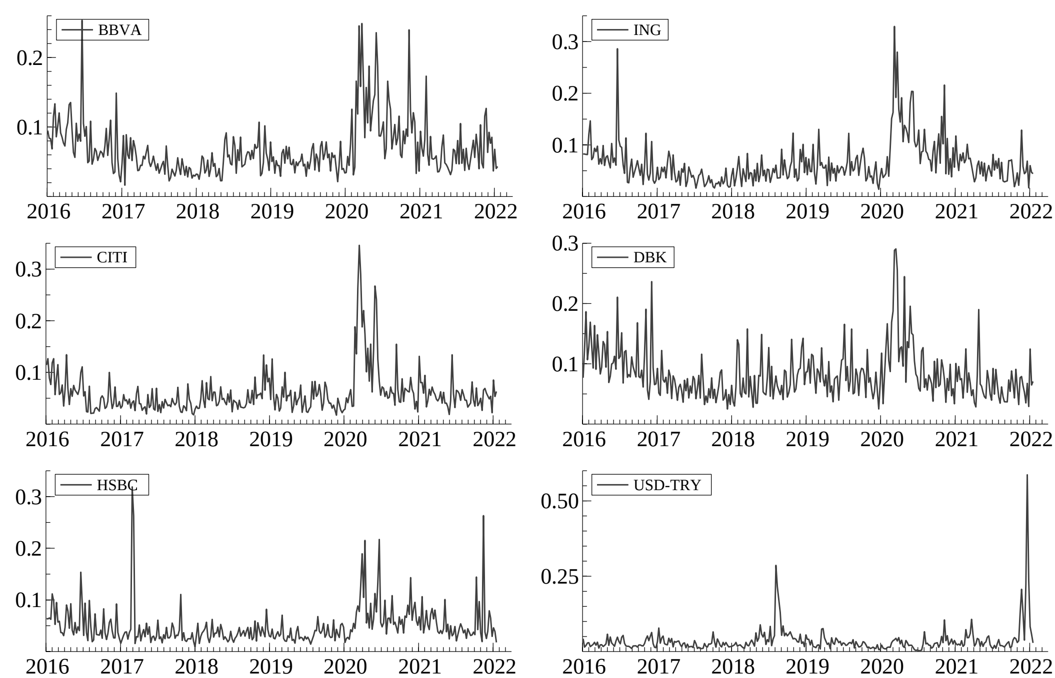

Fig. 2. Time series plots for log-range data of western panel

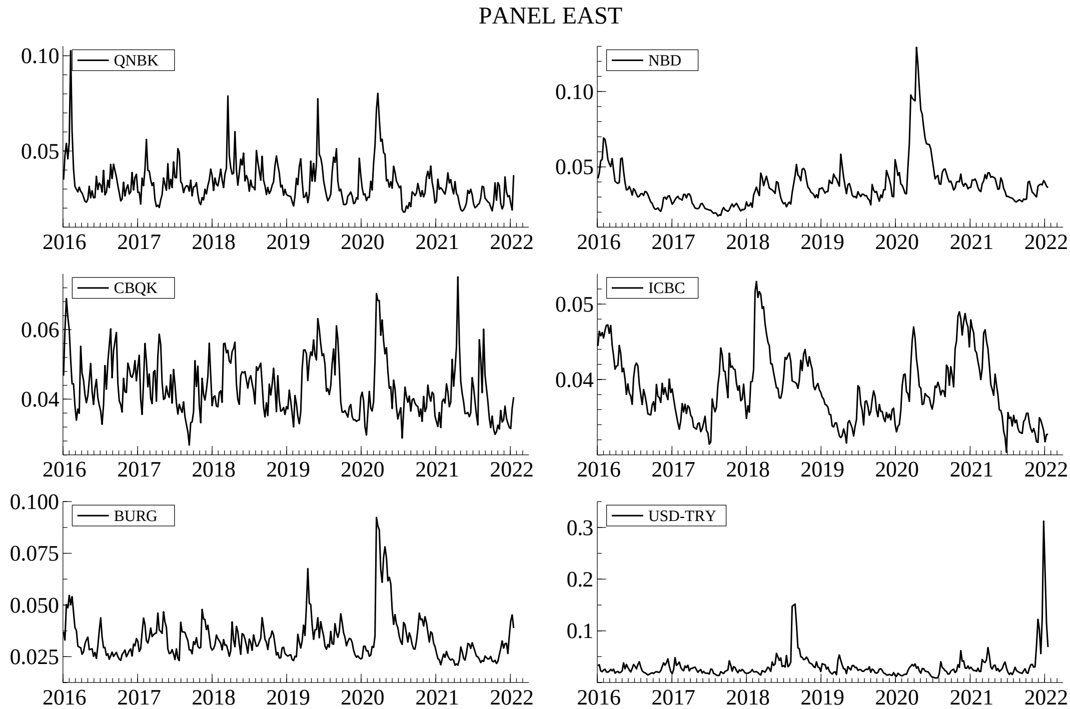

Fig. 3. Time series plots for ECARR volatilities of eastern panel

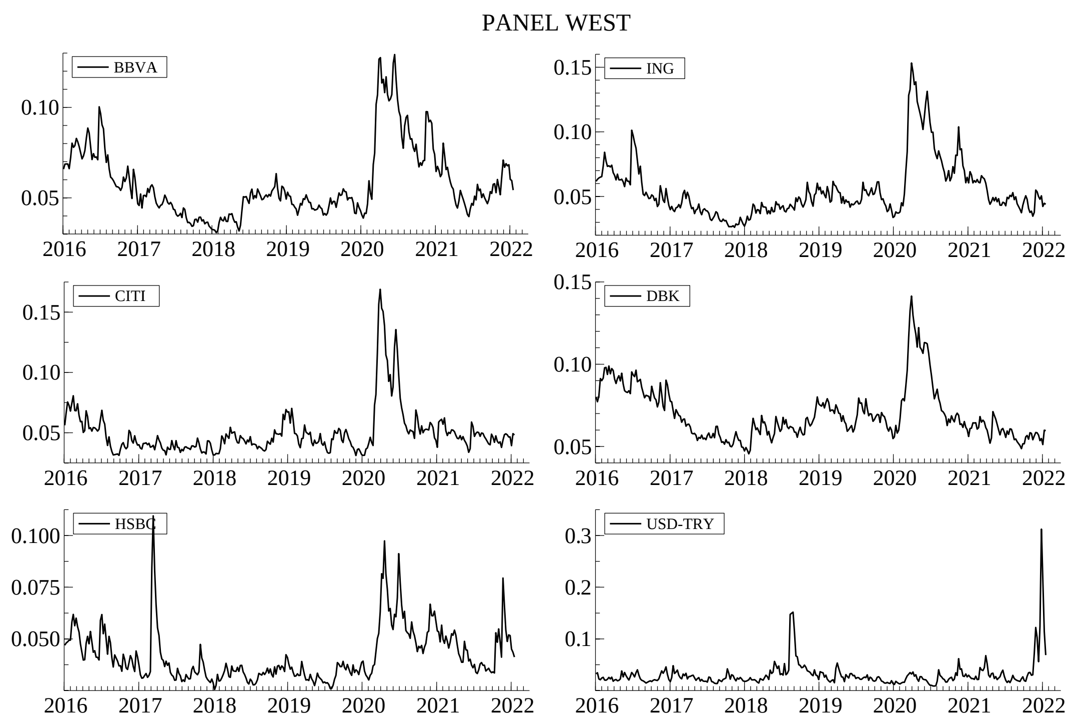

Fig. 4. Time series plots for ECARR volatilities of western panel

tests. ADF and PP statistics show that almost all volatility series are stationary at a 10% confidence level. But ERS statistics indicate that GCARR volatilities are not stationary whereas ECARR volatilities are stationary. Therefore, we apply connectedness analysis via ECARR volatilities.

Figure 3 and Figure 4 illustrate time-series graphs of ECARR(1,1) volatility data for all variables. Findings show that the financial asset with the highest volatility is the USD-TRY exchange rate in both panels. We can say that all bank stock volatility, except USD-TRY, has high volatility during March 2020, when the Covid-19 pandemic started. In addition, the banks in the western panel responded to the pandemic shock more than the eastern banks. One can state that the shock experienced in USD-TRY exchange rate volatility in December 2021 caused a reaction in BURGAN in the eastern panel, and in BBVA and HSBC stocks in the western panel. Another significant shock in the USD-TRY exchange rate volatility appeared in August 2018. The effects and results of shocks on connectedness and volatility pass-through are available in the following section.

Table 2. The estimation of CARR(1,1) volatility models

Bank	Model	ω	α	β	AIC	BIC	LLH	LB	KS
				Eastern					
QNBK	GCARR	0.0042	0.1715	0.3671	–4.443	–4.414	–699.5	41.99	0.051
		(0.0016)	(0.0467)	(0.1477)				[0.227]	[0.808]
	ECARR	0.0082	0.3403	0.3497	–4.556	–4.526	–717.1	41.04	0.287
		(0.0042)	(0.1125)	(0.1895)				[0.259]	[0.000]
NBD	GCARR	0.0012	0.0802	0.7547	–4.169	–4.139	–656.5	41.56	0.048
		(0.00078)	(0.0249)	(0.0784)				[0.241]	[0.865]
	ECARR	0.0022	0.1600	0.7510	–4.338	–4.309	–683.0	40.53	0.284
		(0.0020)	(0.0653)	(0.1106)				[0.277]	[0.000]
CBQK	GCARR	0.0059	0.1117	0.4811	–3.869	–3.839	–609.5	27.23	0.054
		(0.0031)	(0.0396)	(0.1870)				[0.853]	[0.745]
	ECARR	0.0121	0.2330	0.4455	–3.961	–3.932	–624.0	27.26	0.303
		(0.0092)	(0.1058)	(0.2850)				[0.852]	[0.000]
ICBC	GCARR	0.0027	0.0517	0.7452	–4.114	–4.085	–648.0	47.21	0.044
		(0.0024)	(0.0300)	(0.1594)				[0.099]	[0.913]
	ECARR	0.0030	0.0880	0.8174	–4.157	–4.128	–654.7	44.78	0.300
		(0.0049)	(0.0754)	(0.1865)				[0.149]	[0.000]
BURG	GCARR	0.0026	0.1093	0.5984	–4.380	–4.350	–689.5	26.62	0.047
		(0.0013)	(0.0341)	(0.1217)				[0.872]	[0.865]
	ECARR	0.0055	0.2221	0.5726	–4.508	–4.478	–709.6	24.37	0.300
		(0.0038)	(0.0913)	(0.1826)				[0.929]	[0.000]
				Western					
BBVA	GCARR	0.0011	0.0929	0.7459	–3.396	–3.367	–535.6	30.51	0.041
		(0.0011)	(0.0371)	(0.1024)				[0.726]	[0.950]
	ECARR	0.0020	0.1755	0.7574	–3.437	–3.408	–542.0	30.98	0.303
		(0.0028)	(0.0928)	(0.1321)				[0.706]	[0.000]
DBK	GCARR	0.0020	0.0608	0.8006	–2.963	–2.933	–467.8	36.00	0.064
		(0.0016)	(0.0265)	(0.0848)				[0.468]	[0.545]
	ECARR	0.0035	0.1227	0.8035	–3.016	–2.986	–476.1	35.13	0.303
		(0.0042)	(0.0690)	(0.1165)				[0.509]	[0.000]

End of Table 2

Bank	Model	ω	α	β	AIC	BIC	LLH	LB	KS
HSBC	GCARR	0.0020 (0.0013)	0.0978 (0.0360)	0.6793 (0.1192)	–3.944	–3.9152	–621.4	33.93 [0.567]	0.063 [0.545]
	ECARR	0.0039 (0.0035)	0.1779 (0.0897)	0.6951 (0.1631)	–4.069	–4.039	–640.9	33.74 [0.576]	0.309 [0.000]
ING	GCARR	0.0014 (0.0011)	0.1027 (0.0344)	0.7124 (0.0976)	–3.514	–3.484	–554.0	32.81 [0.621]	0.057 [0.678]
	ECARR	0.0024 (0.0028)	0.1960 (0.0871)	0.7228 (0.1277)	–3.583	–3.55	–564.9	32.15 [0.652]	0.287 [0.000]
CITI	GCARR	0.00272 (0.0016)	0.1136 (0.0348)	0.6302 (0.1176)	–3.664	–3.635	–577.6	28.99 [0.790]	0.048 [0.864]
	ECARR	0.0054 (0.0045)	0.2286 (0.0915)	0.6200 (0.1632)	–3.729	–3.699	–587.6	28.39 [0.812]	0.284 [0.000]
				Forex					
USD/ TRY	GCARR	0.0023 (0.0010)	0.2355 (0.0449)	0.3233 (0.1214)	–4.763	–4.733	–749.4	25.77 [0.896]	0.040 [0.865]
	ECARR	0.0042 (0.0024)	0.4542 (0.1140)	0.3351 (0.1583)	–4.903	–4.874	–771.4	25.68 [0.899]	0.284 [0.000]

Notes. LLH — Log-likelihood, LB — Ljung–Box test. The values in parenthesis are standard errors. The corresponding p-values with the test statistics are in brackets.

6. Empirical findings of TVP-VAR connectedness

Antonakakis et al. (2020) consider the benchmark values for forgetting factors provided by Koop and Korobilis (2014) study, where the TVP-VAR[3] forgetting factor is 0.99 and the EWMA forgetting factor is 0.96. Therefore, I use the same forgetting factors' values while estimating the TVP-VAR model with Minessota Prior which is applied in the studies by Antonakakis et al. (2020) and Korobilis, Yilmaz (2018). Table 3 presents the calculation of whole sample volatility spillover indices, as well as their decomposition as receivers and transmitters among Eastern and Western Banks' stocks and USD-TRY exchange rates separately. The results in the total connectedness indices (TCI) tables are derived from a 2nd order TVP-VAR model through generalized error variance decompositions with a forecast horizon of 10 days. The table reports the relative contribution of the asset return volatility shocks given in the columns to the variance of the forecast error for the asset return volatility in the rows, as a percentage. Each cell in the directional 'FROM' others column reports the contribution of other assets to each asset's total variance (forecast error). Each cell in the directional 'TO' other row reports the sum of each asset's contributions to the variance of the forecasting errors of all other assets. The 'NET' directional connectedness row reports the difference between the corresponding cells in the 'TO' row and the 'FROM' column. The total connectedness index, the number in the lower right corner of the table, is equal to the average of the elements of the 'FROM/TO' column/row (Diebold, Yilmaz, 2015).

[3] For TVP-VAR-based connectedness analysis, one can use the R-package *Connectedness Approach*, as well as the online connectedness approach platform prepared by David Gabauer. The website is https://davidgabauer.shinyapps.io/connectedness_approach/.

Table 3 reports the spillover results. The dynamic total connectedness indices (TCI) are 26.72 and 54.75% for eastern and western panels respectively, which means around 27 and 55% of the conditional volatility is obtained from other assets on average. These results indicate low connectedness for the assets in the east panel and high connectedness for the assets in the west panel. Diebold and Yilmaz (2015) find a connectedness rate of 78.3% between the stock return volatility of US banks. Although the study includes high-capital banks in the US market, we can accept this as evidence of high connectivity among western banks with high market capitalization traded in stock markets. In this case, it can be considered as the reason why there is no volatility spillover from the exchange rate in the western panel. The lack of spillovers from exchange rate changes to stock returns is in line with previous research which has focused on the second moments of the relevant distributions. Kanas (2000) investigates the interdependence of stock returns and exchange rate changes within the same economy. He considers six industrialized countries and finds evidence of spillovers from stock returns to exchange rate changes for all countries except one. But volatility spillovers from exchange rate changes to stock returns are insignificant for all countries.

Table 3. Averaged dynamic connectedness table

			Panel East: Eastern banks' stocks and USD-TRY				
	QNBK	NBD	CBQK	ICBC	BURG	USD-TRY	FROM others
QNBK	69.37	7.78	10.38	2.18	8.04	2.26	30.63
NBD	5.77	68.25	2.11	5.71	9.98	8.17	31.75
CBQK	10.93	3.11	74.4	2.44	6.08	3.04	25.6
ICBC	3.6	7.01	2.16	76.75	7.05	3.42	23.25
BURG	7.51	16.83	6.1	1.65	62.85	5.06	37.15
USD-TRY	1.37	5.06	2.12	1.66	1.71	88.07	11.93
TO others	29.19	39.78	22.87	13.65	32.87	21.95	160.31
Inc. own	98.56	108.03	97.27	90.4	95.72	110.03	TCI
NET	–1.44	8.03	–2.73	–9.6	–4.28	10.03	26.72
			Panel West: Western Banks' stocks and USD-TRY				
	BBVA	ING	CITI	DBK	HSBC	USD-TRY	FROM others
BBVA	38.25	23.39	13.7	17.4	5.05	2.21	61.75
ING	23.53	33.82	18.17	18.74	4.57	1.17	66.18
CITI	14.77	23.41	42.19	15.09	3.41	1.12	57.81
DBK	17.9	19.9	16.48	41.69	2.78	1.25	58.31
HSBC	20.81	17.15	13.51	8.99	38.16	1.38	61.84
USD-TRY	6.4	5.51	3.92	2.97	2.34	78.86	21.14
TO others	83.41	89.36	65.78	63.2	18.15	7.13	327.02
Inc. own	121.66	123.18	107.97	104.88	56.32	85.98	TCI
NET	21.66	23.18	7.97	4.88	–43.68	–14.02	54.5

The fact that the average TCI is around 27% in the eastern panel indicates that the financial assets in this panel can be used for portfolio diversification. Moreover, the total risk can be reduced by country diversification. Qatari banks QNBK and CBQK have almost the same connectedness rates. While 69.37% of the forecast error variance in QNBK is due to itself, 2.26% is due to USD-TRY. This is 74.4 and 3.04% for CBQK, respectively. The highest directional volatility transmission from USD-TRY is to NBD with 8.17% and BURG with 5.06%. Since ICBC is a Chinese bank, it has the highest self-connectedness with 76.5%, and the lowest TCI with 90.4%. So, ICBC is the net volatility receiver with 9.6%. In other words, ICBC is the net receiver of shocks from other asset markets in the eastern panel where USD-TRY and NBD are net volatility transmitters.

In the western panel, USD-TRY and HSBC are net volatility receivers whereas BBVA, ING, and DBK are volatility transmitters. Contrary to the eastern panel of USD-TRY, it has a negative net connectedness of 14.02% indicates that there is a net receiver of shocks from other assets. It is noteworthy that while self-connectedness is very low for the bank stocks in the western panel, excluding USD-TRY, the average net directional connectedness of HSBC is negative 43.68%. This shows that HSBC volatility is highly wide open to external shocks.

The net total directional connectedness graphs given in Figure 5 and Figure 6 illustrate that while QNBK was a volatility receiver before the Covid-19 pandemic, it became a volatility transmitter during the pandemic period. NBD is also a diffuser of volatility throughout the pandemic. One can observe that USD-TRY has become a volatility receiver with the onset of the pandemic. In the western panel, HSBC is the volatility receiver for the entire period, and USD-TRY is the volatility receiver except for the period of August 2018 and December 2021. In other words, shocks in other financial assets influence error variances of HSBC and USD-TRY. While BBVA and ING are volatility transmitters throughout the entire period, CITI and DBK are volatility transmitters throughout only the Covid-19 period. In both panels, the diagonal elements of the 6×6 matrices show self-connectedness, while other entries are 20 parts of the forecast error variance decomposition of the variables. For example, the entry C_{52} in the eastern panel means that shocks from USD-TRY are responsible for 8.17% of the 10-step forecast error variance of NPD. Likewise, C_{25} entry means that the shocks in NPD are responsible for 5.06% of the 10-step forecast error variance of USD-TRY. Using equation (9), we can reveal which of the variables dominates the other with Net Pairwise Directional Connectedness (NPDC). Each panel has 15 NPDC measures that can be calculated from $\left(N^2 - N\right)/2$, where N is number of variables. But Table 4 only presents the NPDC between USD-TRY and banks' stocks. According to this table, shocks in USD-TRY have a dominative effect on the forecast error variance of bank stocks in the eastern panel, while USD-TRY is a net volatility receiver in the western panel.

Table 4. Net pairwise volatility connectedness between USD-TRY and banks' stocks

USD-TRY ⇔ QNBK	USD-TRY ⇔ NBD	USD-TRY ⇔ CBQK	USD-TRY ⇔ ICBC	USD-TRY ⇔ BURG
0.93	3.08	0.91	1.80	3.34
USD-TRY ⇔ BBVA	USD-TRY ⇔ ING	USD-TRY ⇔ CITI	USD-TRY ⇔ DBK	USD-TRY ⇔ HSBC
–4.19	–4.33	–2.80	–1.72	–0.97

Figure 7 and Figure 8 demonstrate the Total Dynamic Connectedness Index (TDCI) for whole period. When the World Health Organization declared the Covid-19 pandemic on March 11, 2020, TDCI reached its highest values with 72.17% in the western panel. At the almost same time, in the third week of March 2020, TDCI reached its highest values with 55.34% in the eastern panel.

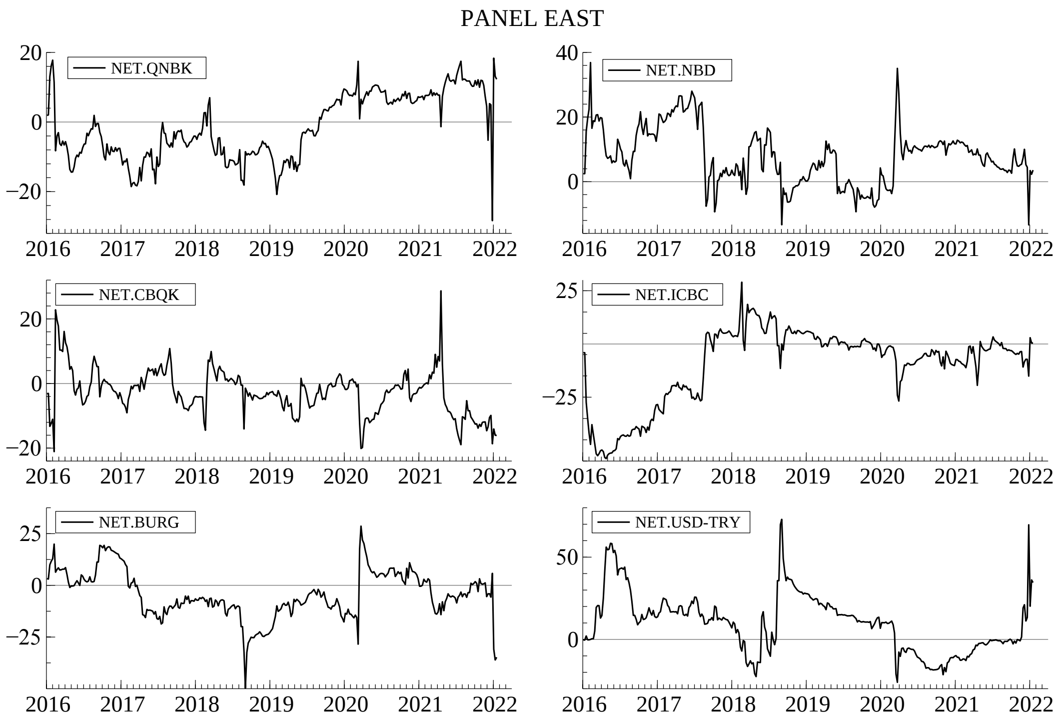

Fig. 5. Net total directional connectedness of eastern panel

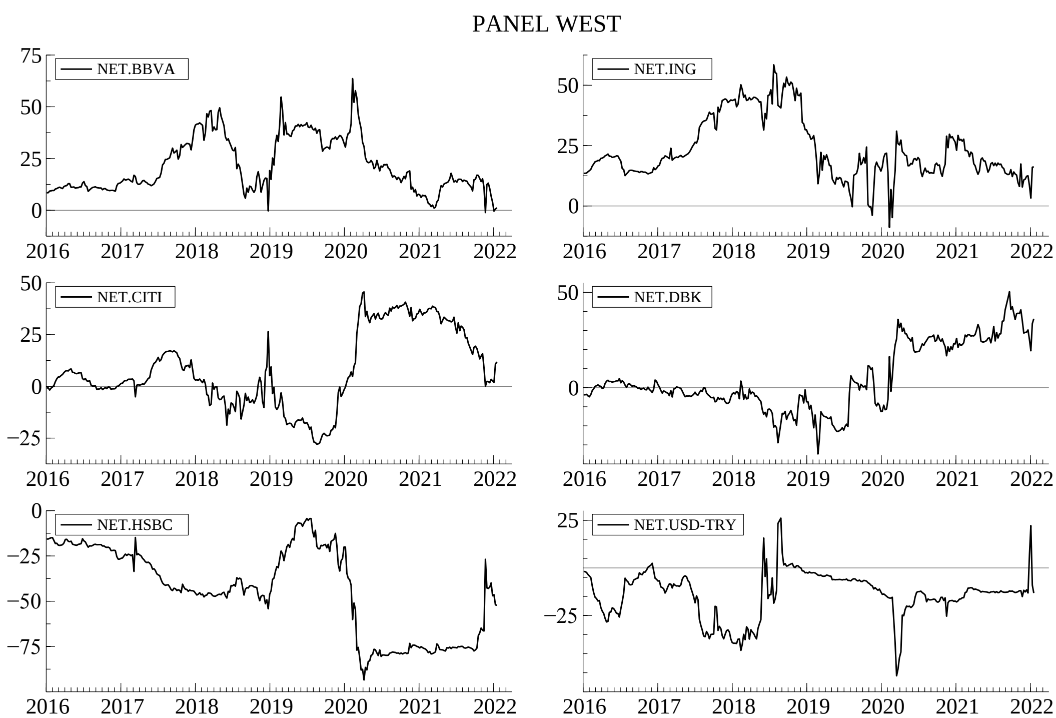

Fig. 6. Net total directional connectedness of western panel

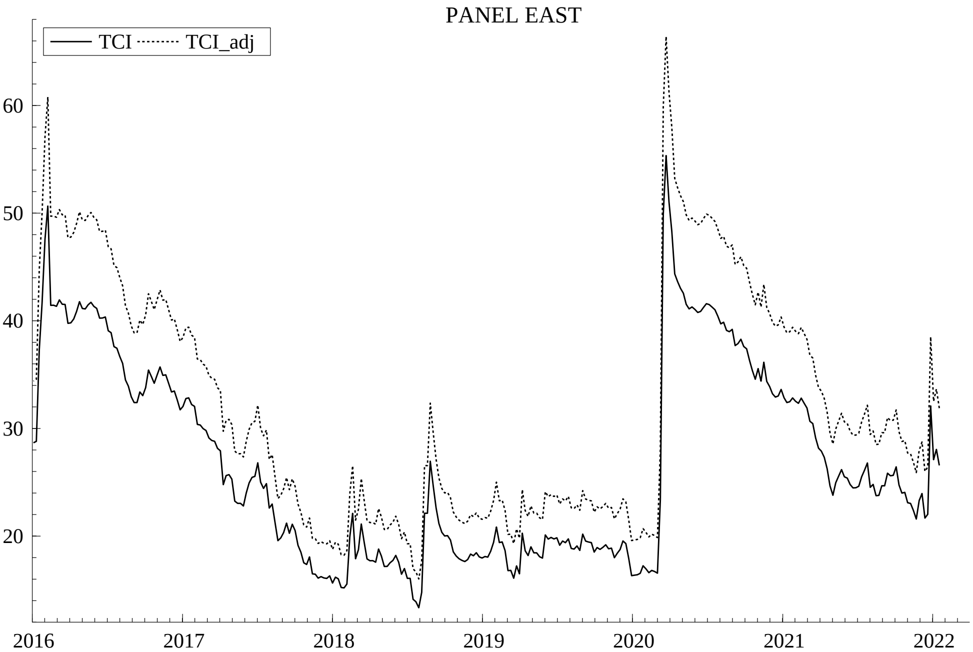

Fig. 7. Total dynamic connectedness index of eastern panel

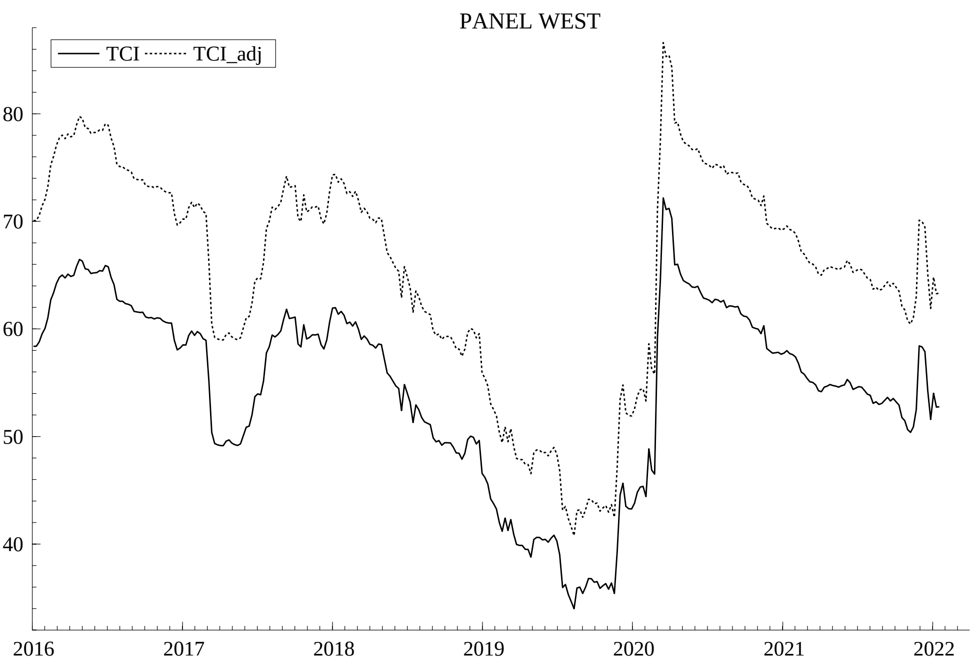

Fig. 8. Total dynamic connectedness index of western panel

When we examine the NPDC graphs in Figure 9 and Figure 10, we can say that USD-TRY is generally a receiver for the shocks in bank stock return volatility during the pandemic period, but this situation disappeared in December 2021. Two important dates that emerged in both panels stand out, these are August 2018 and December 2021. We can summarize these two periods as follows.

- After announcing that the US would impose economic sanctions on Turkey if a US priest imprisoned in Turkey was not released, the dollar, which was 5 TRY at the beginning of August 2018, exceeded the level of 6.5 TRY in a week. On the night of August 12, it tested 7.20 TRY in international markets.

  This increases the TDCI to 26.95% in the eastern panel and the NPCI rates are QNBK (12.44%), NBD (8.23%), CBQK (12.96%), ICBC (17.45%), and BURG (18.61%). Furthermore, the effect of the fluctuation experienced in August increases the NPCI rates between USD-TRY and NBD, USD-TRY and BURG to 27.51 and 35.39%, respectively, in the first week of October 2018.

  In the western panel, the TDCI rate is 51.35%, below the average connectedness index value. Although USD-TRY is a volatility receiver based on average NPCI rates in the western panel, in the second week of August the NPCI rates are BBVA (11.83%), ING (4.52%), CITI (0.50%), DBK (5.01%) and HSBC (1.42%). In the next week, the NPCI rates of CITI (7.17%) and HSBC (9.93%) increase.
- The interest rate discourses of the decision-makers led to four rate cuts in 2021 when inflation continued to rise for eight months on an annual basis. In the decision of the Monetary Policy Committee of the Central Bank of the Republic of Turkey dated 16 December 2021, the policy interest rate was reduced to 14%. With the announcement of the interest rate decision, the USD-TRY peaked at 18.36 on 20 December, then fell to 10.27 with the implicit interventions of the Central Bank.

  In the third week of December 2021, the TDCI rate for the eastern panel reaches 32.08%. The corresponding NPDC values in this period show that the banks with the highest net shock transition from USD-TRY are QNBK (19.57%), NBD (23.90%), CBQK (10.03%), and BURG (16.14%) whereas ICBC is a shock transmitter to USD-TRY with –0.013%.

  The fluctuations in the USD-TRY exchange rate in the last quarter of 2021 changed the TDCI rate of western panel, range from 51.58 to 58.32% between the first week of December and the first week of January 2022. These index values are around the mean. While NPCI rates were BBVA (–3.94%), ING (–3.73%), CITI (–0.94%), DBK (2.44%), and HSBC (–6.94%) in the third week of December 2021, it increases for ING (2.42%), CITI (3.07%) and DBK (26.34%) in the first week of January 2022.

7. Conclusion

The empirical method of this paper is constructed on the TVP-VAR-based Diebold and Yilmaz (2014) spillover index approach proposed by Antonakakis et al. (2020). In this way, the volatility connectedness analysis between the USD-TRY and the stocks of foreign capital banks in Turkey traded in their own country's stock exchanges is revealed. The volatilities of the variables separated as the east panel and the west panel are estimated with the ECARR model (Chou, 2005). The average values obtained from empirical results (26.72% for eastern and 54.75% for western) indicate that the dynamic connectedness index is higher in the west panel. However, according to the net pairwise connectivity values, USD-TRY is a volatility transmitter in the east panel, while it is a volatility receiver in the west panel. Total connectedness in both panels reaches its highest

PANEL EAST

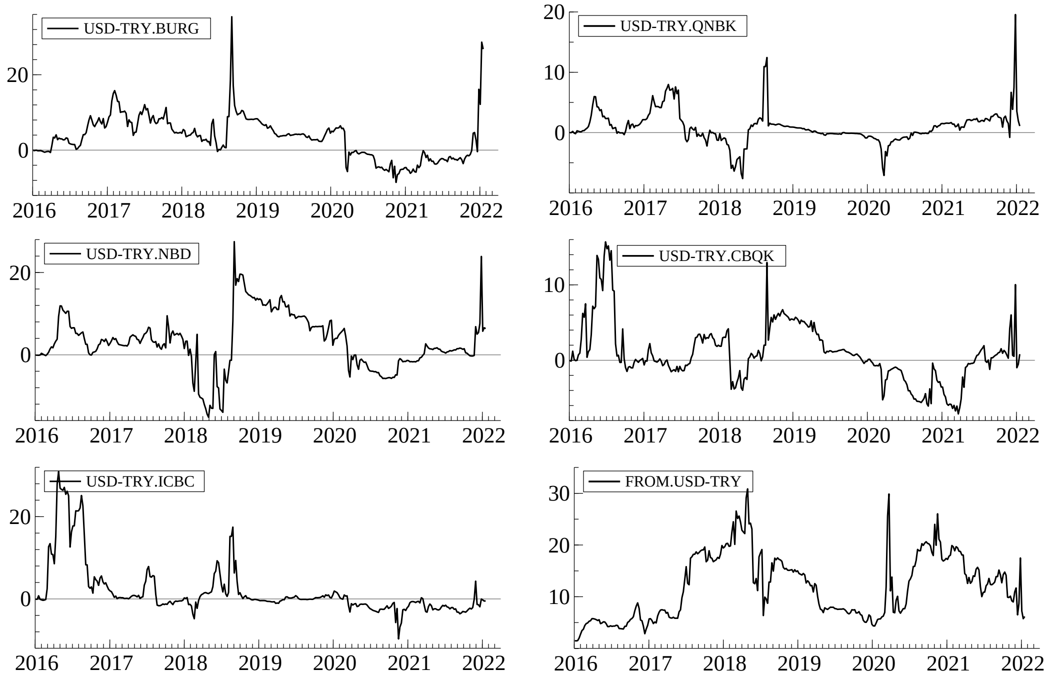

Fig. 9. NPDC between USD-TRY and banks' stocks for eastern panel

PANEL WEST

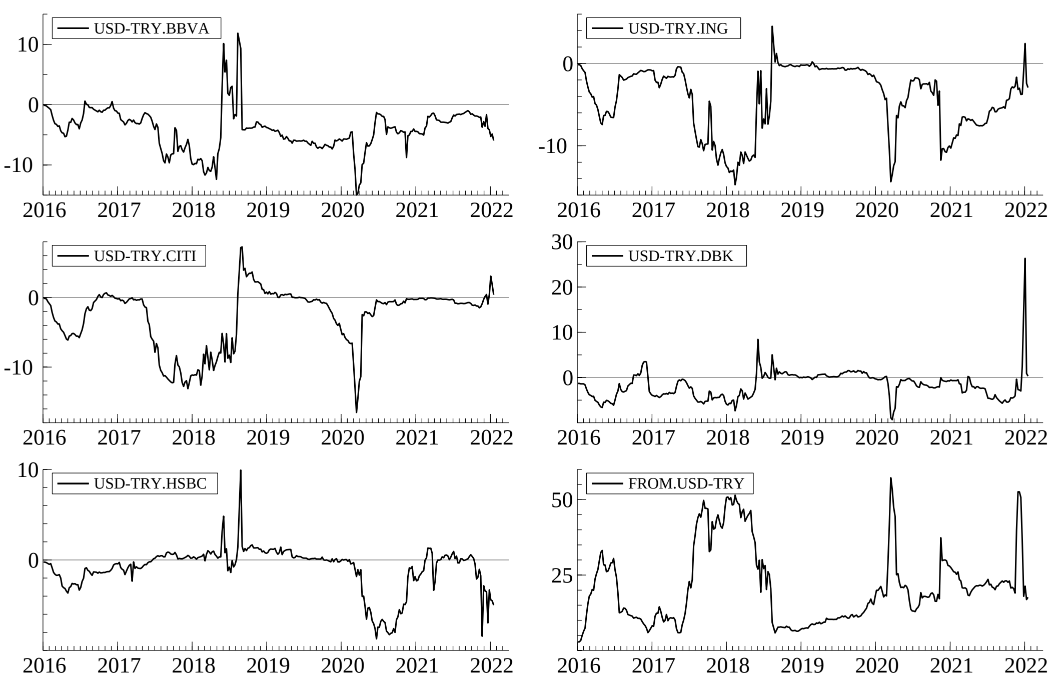

Fig. 10. NPDC between USD-TRY and banks' stocks for western panel

value in the second week of March 2020 when the Covid-19 pandemic was declared. According to the ECARR(1,1) volatility estimation, two prominent periods stand out in the USD-TRY volatility. These are August 2018 and December 2021, when two major shocks in USD-TRY volatility occurred. In both periods, while total connectedness increased in the eastern panel, it was observed to be around the average in the western panel. Although ICBC ranks ninth among foreign banks in terms of asset size in Turkey, the average connectivity values in the eastern panel show that the Chinese origin ICBC is not affected by the shocks in USD-TRY. In the western panel, it is clear that the source of high connectivity is the spread among bank stocks. In particular, HSBC is a very large shock receiver. Likewise, it is seen that the depreciation and shocks in the Turkish Lira, in general, did not have much effect on the western panel. But in both panels, it turns out that deep shocks make the USD-TRY a shock spreader. Another interesting result is that BBVA, which is the owner of the foreign-capital bank with the largest asset size in Turkey, is the shock transmitter against USD-TRY except for the August 2018 period.

The Central Bank of the Republic of Turkey has not determined any target level regarding the exchange rate under the floating exchange rate regime. However, under certain conditions, the Central Bank intervenes directly or indirectly in excessive volatility. In addition to this situation, the effects of political events cause high shocks in the Turkish Lira and increase volatility. Moreover, unhealthy price formations are seen in the foreign exchange market with the low-interest policy that is unrealistic and completely far from economic fundamentals. The interest pressure created by the increasing inflation in the USA increases the possibility of the Turkish Lira losing value. As a result of these and the obtained empirical results from this paper, it is predicted that the effect of deep shocks to be experienced in TRY may affect the stock return risks of foreign capital banks operating in Turkey.

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Appendix A

Table A1. Descriptive statistics of log-range data

	CBQK	QNBK	NBD	ICBC	BURG	BBVA	ING	CITI	DBK	HSBC	USD-TRY
Mean	0.051	0.039	0.044	0.046	0.040	0.068	0.065	0.060	0.083	0.049	0.036
Median	0.044	0.032	0.034	0.042	0.032	0.058	0.055	0.050	0.075	0.039	0.027
Standard deviation	0.027	0.025	0.037	0.020	0.029	0.039	0.042	0.042	0.042	0.037	0.045
Variance	0.001	0.001	0.001	0.000	0.001	0.001	0.002	0.002	0.002	0.001	0.002
IQR	0.035	0.024	0.028	0.022	0.025	0.040	0.038	0.032	0.042	0.028	0.022
Range	0.165	0.221	0.354	0.159	0.297	0.237	0.315	0.329	0.266	0.310	0.584
Minimum	0.000	0.000	0.000	0.010	0.003	0.017	0.014	0.017	0.025	0.009	0.003
Maximum	0.165	0.221	0.354	0.169	0.300	0.253	0.329	0.346	0.291	0.319	0.586
Skewness	1.100	2.710	3.710	1.570	3.540	2.110	2.550	3.240	1.810	3.550	7.550
Standard error skewness	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138
Kurtosis	1.360	12.60	22.10	4.770	23.30	6.160	9.910	14.30	4.840	17.50	78.60
Standard error kurtosis	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275
Shapiro–Wilk W	0.924	0.789	0.692	0.897	0.727	0.816	0.786	0.692	0.858	0.667	0.424
Shapiro–Wilk *p*-value						< 0.001					

Appendix B

Table B1. Normality, stationarity and autocorrelation tests for CARR(1,1) volatilities

		Skewness	Excess kurtosis	JB	ERS	PP	ADF	Q(10)	$Q^2(10)$
QNBK	G	2.159***	8.049***	1088.3***	–2.693***	–7.548***	–7.556***	283.8***	189.1***
	E	2.225***	8.599***	1222.5***	–5.686***	–7.836***	–7.744***	263.2***	169.1***
NBD	G	2.404***	7.976***	1131.1***	**–1.298**	–3.684***	–3.763***	975.5***	842.5***
	E	2.589***	9.736***	1585.9***	–3.547***	–3.459***	–3.660***	978.6***	836.2***
CBQK	G	0.983***	0.984***	63.06***	**–1.206**	–6.806***	–6.778***	348.3***	329.1***
	E	0.870***	0.635**	44.75***	–5.064***	–6.945***	–6.975***	309.9***	286.4***
ICBC	G	2.491***	10.90***	1873.4***	**0.132**	–7.302***	–7.345***	630.7***	536.1***
	E	0.703***	**0.008**	25.80***	–1.716*	–3.409**	–3.369**	934.2***	913.2***
BURG	G	2.324***	7.268***	970.6***	**–1.444**	–5.060***	–5.129***	623.5***	577.5***
	E	2.471***	8.568***	1275.8***	–3.984***	–5.069***	–5.155***	583.3***	533.9***
BBVA	G	1.304***	1.241***	108.6***	**–0.747**	–3.386**	–3.265**	1191.0***	1082.4***
	E	1.357***	1.602***	129.5***	–2.431**	–2.636*	**–2.477**	1256.6***	1159.3***
ING	G	1.835***	3.740***	358.0***	**–1.181**	–3.186**	–3.126**	1109.1***	995.3***
	E	1.923***	4.256***	429.1***	–3.016***	–2.682*	–2.605*	1149.1***	1033.5***
CITI	G	2.999***	10.84***	2001.7***	–1.675*	–3.819***	–4.060***	889.9***	766.0***
	E	3.161***	12.18***	2457.4***	–3.900***	–3.629***	–3.981***	887.5***	757.2***
DBK	G	1.578***	2.389***	204.4***	**–0.097**	–4.210***	–4.188***	1131.6***	1034.7***
	E	1.472***	2.481***	193.3***	–2.086**	–2.600*	**–2.490**	1224.7***	1160.2***
HSBC	G	1.734***	3.862***	351.5***	**–1.251**	–5.058***	–4.982***	670.9***	474.4***
	E	1.755***	4.107***	380.6***	–3.634***	–4.600***	–4.500***	707.7***	510.8***
USD	G	6.227***	52.11***	37437.9***	–2.464**	–6.346***	–2.572*	329.5***	120.6***
	E	6.190***	51.35***	36381.2***	–2.686***	–6.225***	–2.572*	337.2***	125.0***

Note. G — Gumbel CARR Volatility; E — Exponential CARR Volatility.
Significance: *** — < 0.01, ** — < 0.05 and ** — < 0.10. Bolds are non-significant.