*Yakup Arı*[a]
*Hakan Kurt*[b]
*Harun Uçak*[c]

JEL classification: L8, C58, F42
Preliminary statement
https://doi.org/10.32910/ep.75.4.1

# Volatility connectedness across global e-commerce stocks

## Abstract

*This paper studies the volatility connectedness between the stock prices of e-commerce companies. For that matter, we implement the TVP-VAR-Based connectedness procedure to unearth the dynamic structure of volatilities. This approach helps us to determine the volatility spillover between assets that are risk receivers or risk transmitters. We utilize the daily log-return data of the largest e-commerce companies by market cap. The data set consists of the daily open, close, high, and low prices of stocks between 2019-01-02 and 2022-12-23. We obtain the volatility of stocks using the Garman-Klass range-based approach. The findings reveal that the average total connected index is relatively high by 65.45%, which means that the forecasting error variance in the variables is due to the transmission and connectedness between these variables. Furthermore, net pairwise directional connectedness results evidence that the most dominant stock is Amazon within the network. Ultimately, we find the strongest bilateral volatility interconnectedness to occur between the stocks of Alibaba and Jingdong Mall.*

**Keywords:** E-commerce, Diebold-Yılmaz Connectedness, Garman-Klass Volatility, TVP-VAR

---

[a] Y. Arı, Ph.D., Associate Professor, Alanya Alaaddin Keykubat University, Department of Economics (e-mail: yakup.ari@alanya.edu.tr).
[b] H. Kurt, M.A., Research Assistant, Alanya Alaaddin Keykubat University, Department of Economics (e-mail: hakan.kurt@alanya.edu.tr).
[c] H. Uçak, Ph.D., Full Professor, Alanya Alaaddin Keykubat University, Department of Economics (e-mail: harun.ucak@alanya.edu.tr).
The paper was received on 12.06.2023. It was accepted for publication on 13.12.2023.

## 1. INTRODUCTION

Remarkable developments have been witnessed in the 20th century, one of which was the advent of the Internet around the late 1980s and early 1990s. As a useful platform for various activities, the Internet has altered the venue through which consumers shop and purchase goods and services along with how businesses offer their products (Dhanapal et al., 2015). Resultingly, companies incorporated the Internet into their day-to-day business strategies to access the growing marketplace, ultimately resulting in the emergence of electronic commerce (e-commerce, thereafter) (Rosário & Raimundo, 2021). E-commerce is envisioned as a potential new engine for future economic growth (Shaw et al., 2022). Worldwide e-commerce sales volume was 7.4 percent of total retail sales in 2015 and reached 18.8 percent in 2021 with the estimation that it will grow to make up 24 percent of total worldwide retail sales in 2026 (Statista, 2023). Especially after the emergence of the COVID-19 pandemic caused by the novel and highly infectious SARS-CoV-2 coronavirus and accompanying interventions to curtail its further human-to-human transmission, e-commerce sales volume rose dramatically as consumers increasingly turned to online shopping (Nguyen et al., 2021). The pandemic-induced shift on the part of consumers from going to brick-and-mortar stores to online shopping also led to a sharp increase in revenues of consumer-oriented e-commerce businesses. E-commerce giants such as Amazon, JD.com, and Alibaba achieved revenue increases of up to 70 percent during the 2019-2021 period (UNCTAD, 2022).

Despite e-commerce's sectoral importance as a source of growth and the COVID-19-fuelled boom in sales, the resumption of in-store shopping as a result of the gradual abolishment of COVID-19 restrictions, the emergence of Russia-Ukraine conflict on 24 February 2022 and accompanying inflationary pressures on a global scale, associated policy rate hikes on the part of central banks in response to surging inflation and rising fears of global recession caused the volatility of e-commerce stocks to surge due to high uncertainty and turbulence in the financial markets (Bloomberg, 2022). That, in turn, leads to a rise in connectedness across financial markets because of the risk of likely transmission and spillover effects in returns and volatilities (Umar et al., 2023). Comprehending these spillovers is necessary for investors, portfolio managers, and policymakers to make educated and informed decisions.

Against this background, the return and volatility connectedness across financial markets in general; individual stocks, currencies, and commodities, in particular, has recently become a topic of interest. Given its unparalleled nature, the majority of recent studies surfaced around the COVID-19 global health crisis (Nasreen et al., 2021). For instance, by using the connectedness measures of Diebold and Yilmaz (2009, 2012, 2014), Costa et al. (2022) study volatility connectedness across 11 sectoral indices in the context of the US and discover that the increase in total connectedness is more pronounced starting from the early stages of the international spread to the mid-summer of 2020. Bouri et al. (2021) investigate the impact of the COVID-19 pandemic on international financial markets by focusing on different asset classes during and before the outbreak and report that financial connectedness became particularly strong after the advent of the pandemic. Bissoondoyal-Bheenick et al. (2021) examine whether the connectedness measures act differently for countries that previously suffered SARS (2003) related deaths in the context of the G-20 countries and show that even though connectedness across global financial markets intensifies with the advent of the COVID-19 pandemic, it is much lower for those countries with SARS related deaths. Cagli et al. (2023) investigate volatility spillover and dynamic connectedness between the daily prices of agricultural commodities and the stock prices of the firms operating in the agricultural industry via the novel TVP-VAR joint connectedness method of Balcilar et al. (2021) and evidence that stock prices of agri-businesses are the net transmitters of shocks while agricultural futures end up being net receivers of volatility. And that connectedness between these asset classes increased during turbulent episodes of the Great Recession of 2008-2009 and the COVID-19 pandemic.

There also exists recently emerging studies around the Russia-Ukraine armed conflict of

February 24th, 2022. Taking into account the combined roles of both Russia and Ukraine being significant players in the global commodity markets coupled with the fact that connectedness in financial markets tends to rise during tumultuous episodes of extreme events motivate researchers to study the connectedness in regional and international financial markets and across different asset classes in the brink of such events. The study conducted by Alam et al. (2022) investigates how the ongoing armed conflict between Russia and Ukraine has affected the interrelationships over time among five different commodities: crude oil, natural gas, platinum, silver, and gold, as well as the stock markets of the G7 countries and the emerging economies of BRIC. Adekoya et al. (2022) analyze the dynamic connectedness between oil and five distinctive asset classes (i.e., bonds, bitcoin, the US dollar, gold, and stocks) during different periods throughout the ongoing conflict. Shahzad et al. (2023) study the dynamics of the connectivity in the context of the non-renewable energy and precious metals markets emanating from financial instability and geopolitical risks caused by the ensuing Russia-Ukraine war via the TVP-VAR procedure of Antonakakis and Gabauer (2017).

Critical evaluation of the existing literature suggests that during extreme events such as the SARS outbreak of 2003, the Great Recession of 2008-2009, the highly infectious COVID-19 pandemic, and the ongoing Russo-Ukrainian armed conflict of February 24, 2022, there is a palpable increase in the transmission of returns and volatility across financial markets as whole and various asset classes, which can be attributed to the growing interconnectedness brought on by globalization and the liberalization policies (see Chirilă, 2022). In light of this, our paper studies the volatility connectedness in the context of select e-commerce stocks via the TVP-VAR procedure of Antonakakis et al. (2018, 2020) by exploiting a time frame that encompasses both the COVID-19 pandemic and the Russia-Ukraine war, as in Cagli et al. (2023), and is the first to carry out such an analysis in the context of e-commerce companies.

The structure concerning the remainder of this paper is designed as follows: Section 2 illustrates data and methodology. Section 3 portrays empirical findings. Ultimately, Section 4 concludes the study herein.

## 2. MATERIALS AND METHODS

### 2.1 Data Set

The data set consists of the stock prices of e-commerce companies with the highest market capitalization in the world. We determine the ranking of companies by market caps according to the site https://companiesmarketcap.com/. The market caps, rankings, and countries of the companies are illustrated in Table 1. We select e-commerce companies that have a market cap of over 15 billion USD. However, we are able to select ten of them since the data as to some of the companies with the largest market cap do not encompass the COVID-19 period. In our study, it is one of our aims to examine the effects of the COVID-19 pandemic while examining the volatility pass-through of the select constituents. Therefore, stock price data should cover the pandemic period. Consequently, some companies[1] are not included in the study. We obtained daily high (h), low (l), open (o), and close (c) (hereinafter OHLC) prices of the companies' stocks from https://www.investing.com/. The dataset includes daily OHLC observations of stock prices ranging from 2 January 2019 to 23 December 2022. The selection of this temporal interval is predicated on creating an optimum period for the existing stock pricing data to avoid missing values. Moreover, this period encompasses a spectrum that integrates pre-pandemic and pandemic timeframes, specifically including the epoch characterized by the emergence and proliferation of the COVID-19 virus.

### 2.2 Construction of Range-Based Volatilities

The network of e-commerce companies may have a connection through their contractual obligations and agreements recorded on their balance sheets. Thus, high-frequency analysis

[1] Companies that are left out in the analysis are Meituan, JD Health Coupang, and Chewy.

**Table 1:** E-commerce companies

| Global Rank | Name | Symbol | Marketcap | Stock Market | Country |
|---|---|---|---|---|---|
| 1 | Amazon | AMZN | $ 869,694,963,712 | NASDAQ | United States |
| 2 | Alibaba | BABA | $ 232,766,717,952 | NYSE | China |
| 3 | Meituan | 3690.HK | $ 145,427,668,071 | NASDAQ | China |
| 4 | Pinduoduo | PDD | $ 106,246,692,864 | NASDAQ | China |
| 5 | Jingdong Mall | JD | $ 101,164,179,456 | NASDAQ | China |
| 6 | MercadoLibre | MELI | $ 44,175,015,936 | NASDAQ | Argentina |
| 7 | Shopify | SHOP | $ 42,882,150,400 | NYSE | Canada |
| 8 | JD Health | 6618.HK | $ 29,487,888,191 | NASDAQ | China |
| 9 | Copart | CPRT | $ 28,820,912,128 | NASDAQ | United States |
| 10 | Sea (Garena) | SEA | $ 28,041,959,424 | NYSE | Singapore |
| 11 | Coupang | CPNG | $ 26,784,638,976 | NASDAQ | South Korea |
| 12 | eBay | EBAY | $ 21,798,610,944 | NASDAQ | United States |
| 13 | Chewy | CHWY | $ 16,646,043,648 | NASDAQ | United States |
| 14 | Etsy | ETSY | $ 15,954,835,456 | NASDAQ | United States |

Source: Authors' own calculation

of the connectedness of e-commerce companies might seemingly mandate a high-frequency balance sheet and relevant information that is often not available. Fortunately, stock prices embody all of this information. So, we can use stock prices to reveal volatility connectedness in the network. We obtain the volatility through range-based volatility, as in the studies of Diebold and Yilmaz (2015) and Korobilis and Yılmaz (2018). We generate a daily range-based volatility forecast for a given firm on a given day, using the natural logarithms of the daily OHLC prices. Applying the following equation proposed by Garman and Klass (1980)[2], we obtain range-based Garman and Klass volatility estimates:

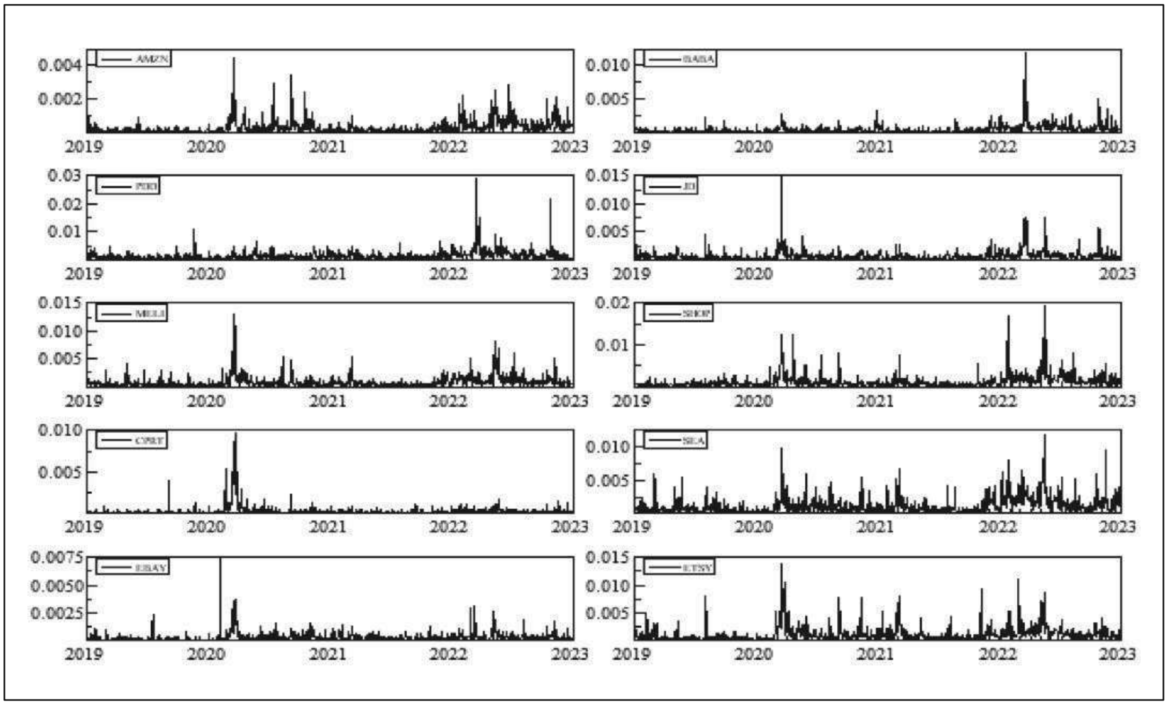
$$\sigma_{gk}^2 = 0{:}\ 511(h-l)^2 - 0{:}\ 19[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0{:}\ 383(c-o)^2$$

Figure 1 shows the time-series plots of range-based Garman and Klass volatilities. Except for BABA and PDD, there is a significant surge in all stock volatilities in the March 2020 period when the Covid-19 health crisis was officially declared a pandemic. In addition, a significant increase is observed in all stock volatilities, except for CPRT, in February 2022, when the Russo-Ukrainian crisis began.

Table 2 presents summary statistics and correlation values for the volatility series. Spearman correlation statistics illustrate that there exists a positive and significant relationship between

[2] Garman and Klass (1980) proposed a volatility estimation method under two assumptions. The first one is that the volatility process is a Brownian motion with zero drift. The latter is that there are no opening jumps, meaning that the opening price is equivalent to the close of the previous period. The comparison results demonstrate that the efficiency of the Garman and Klass estimator is 7.4 times the efficiency of the Closed-to-closed estimator. On range-based volatility, see, for example, Ari (2022a).

**Figure 1:** Time series plots of range-based garman-klass volatilities



Source: Authors' own calculation

volatilities. It is seen that the highest correlation value occurs between AMZN and SHOP whereas the lowest correlation transpires between CPRT and PDD, as highlighted in blue and red respectfully. As the statistically significant skewness and kurtosis values show, all assets exhibit asymmetry and a heavier tail in their volatility distributions in comparison to the normal distribution. The Jarque-Bera test significantly rejects the null hypothesis of the normal distribution for all realized volatility time series. In addition, the weighted Ljung-Box statistic for serial correlation (weighted portmanteau tests) up to 20 lags shows a significant autocorrelation in all volatility series. Moreover, the results of the ERS test are statistically significant and show stationarity in all cases, refuting the null hypothesis of the existence of a unit root in range-based volatility series. Thus, we can conclude that the series is convenient for the TVP-VAR model.

## 2.3 TVP-VAR-Based Connectedness Approach

Diebold and Yilmaz's (2009, 2012, 2014) connectedness methodology offers both static and dynamic time series network analysis while revealing the connections inside a given network. The method has gained popularity recently as it allows researchers to draw conclusions. It is an effective computer technique that calculates the dynamic interconnectivity between variables as this is crucial to capture cross-market spillovers during market turbulence and crises. The dynamic technique uses an estimated rolling window VAR approach, while the static approach applies a Vector Autoregressive (VAR) model over the full dataset. In this study, we employ a dynamic connectedness technique based on Antonakakis et al. (2018, 2020) Time-Varying Parameter Vector Autoregressions (TVP-VAR). They suggest a strategy for avoiding data loss, which includes the working sample information utilized in the rolling window VAR technique. The following additional benefits are associated with the TVP-VAR-based connectivity strategy according to Bouri et al. (2021): (i) The underlying Kalman filter causes outlier insensitivity, (ii) no loss of observation, (iii) no need to determine the rolling window size arbitrarily, and (iv) can also be employed for low-frequency datasets.

**Table 2:** Summary statistics of range-based garman-klass volatilities

| Statistics | AMZN | BABA | PDD | JD | MELI | SHOP | CPRT | SEA | EBAY | ETSY |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.000 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 |
| Variance | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Skewness | 3.966 | 7.922 | 7.173 | 6.631 | 5.134 | 5.127 | 8.668 | 2.812 | 6.751 | 3.638 |
| Kurtosis | 24.431 | 114.967 | 82.588 | 71.754 | 39.875 | 41.457 | 92.965 | 12.171 | 77.875 | 19.178 |
| JB | 27601.3 | 563433 | 293944 | 222741 | 70925.8 | 76295 | 374114 | 7519.69 | 261324 | 17600.4 |
| ERS | -3.214 | -8.083 | -6.830 | -6.930 | -7.733 | -7.608 | -6.959 | -5.332 | -7.233 | -7.805 |
| Q(20) | 1195.41 | 870.699 | 808.396 | 720.206 | 1322.68 | 926.839 | 1864.87 | 944.588 | 471.374 | 1010.09 |
| Q2(20) | 191.266 | 63.263 | 191.294 | 98.638 | 767.119 | 109.638 | 979.346 | 243.098 | 30.229 | 312.606 |
| Spearman | AMZN | BABA | PDD | JD | MELI | SHOP | CPRT | SEA | EBAY | ETSY |
| AMZN | 1.000 | | | | | | | | | |
| BABA | 0.571 | 1.000 | | | | | | | | |
| PDD | 0.399 | 0.515 | 1.000 | | | | | | | |
| JD | 0.471 | 0.619 | 0.511 | 1.000 | | | | | | |
| MELI | 0.589 | 0.523 | 0.391 | 0.458 | 1.000 | | | | | |
| SHOP | 0.623 | 0.508 | 0.368 | 0.404 | 0.586 | 1.000 | | | | |
| CPRT | 0.474 | 0.371 | 0.271 | 0.364 | 0.447 | 0.436 | 1.000 | | | |
| SEA | 0.511 | 0.481 | 0.431 | 0.479 | 0.515 | 0.521 | 0.399 | 1.000 | | |
| EBAY | 0.583 | 0.419 | 0.335 | 0.384 | 0.465 | 0.459 | 0.462 | 0.421 | 1.000 | |
| ETSY | 0.557 | 0.459 | 0.401 | 0.450 | 0.570 | 0.557 | 0.485 | 0.524 | 0.508 | 1.000 |

*Notes:* All statistics are significant at 1% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; and ERS: Elliott, Rothenberg, and Stock (1996) unit-root test. (20) and $Q^2$ (20): Fisher and Gallagher (2012) weighted portmanteau test.

*Source:* Authors' own calculation.

Koop and Korobilis (2014) developed fast estimation procedures that are predicated on the Kalman filter with forgetting factors and are smoother and simulation-free. Antonakakis et al. (2020) applied the very same Kalman filter estimation with forgetting factors in the TVP-VAR model. So, they extended Diebold and Yilmaz's (2014) connectedness approach utilizing the TVP-VAR method by allowing the variance-covariance matrix to vary.

Also, we use the same methodology as Antonakakis et al. (2020) to reveal the time-varying connectedness analysis via the TVP-VAR-based approach. Bayes Information Criteria (BIC) shows us that the TVP-VAR(1) model as expressed in the following equation is the most appropriate:

$$y_t = \mathbf{B}_t z_{t-1} + \varepsilon_t \qquad \boldsymbol{\varepsilon_t} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\Sigma}_t) \tag{1}$$

$$\mathrm{vec}(B_t) = \mathrm{vec}(B_{t-1}) + \upsilon_t \qquad \boldsymbol{\upsilon_t} \sim \boldsymbol{N}(\mathbf{0}, \mathbf{S}_t) \tag{2}$$

wherein $y_t$, $z_{t-1}$ and $\varepsilon_t$ represent $k \times 1$ dimensional vectors, and $\mathbf{B}_t$ and $\mathbf{\Sigma}_t$ are $k \times k$ dimensional matrices, $vec(\boldsymbol{B}_t)$ and $\upsilon_t$ are $k^2 \times 1$ dimensional vectors. $S_t$ are time-varying variance-covariance matrices of which the dimension is $k^2 \times k^2$.

Diebold–Yilmaz's approach is based on the Generalized Forecast Error Variance Decomposition (hereinafter GFEVD) of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). As a result, we must convert TVP-VAR into TVP-VMA because of the Wold representation theorem which states that

$$y_t = \sum_{h=0}^{\infty} \mathrm{B}_{ht} z_{t-h} + \epsilon_{t-h} = \sum_{h=0}^{\infty} \mathrm{A}_{ht} \epsilon_{t-h}$$

where $A_0 = I_k$ and $A_t$ demonstrates a $k \times k$ dimensional time-varying VMA coefficient matrix. So, by applying the h-step forward GFEVD, we may forecast pairwise directional connectedness. The following formula determines how a shock in variable j affects variable i:

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\sum_{h=0}^{H-1} \left(\epsilon_i^T A_{ht} \Sigma_t \epsilon_j\right)^2}{\left(\epsilon_i^T \Sigma_t \epsilon_j\right) \sum_{h=0}^{H-1} \left(\epsilon_i^T A_h \Sigma_t A_{ht}^T \epsilon_i\right)} \quad (3)$$

with $\sum_{j=1}^{m} \tilde{\phi}_{ij,t}^{g}(H) = 1$ and $\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}^{g}(H) = k$. As a result, we can calculate Diebold Yilmaz's (2012, 2014) connectedness measures via GFEVD by applying the following equations.

Equation 4 (***Total Directional Connectedness to Others - TO***): shows the overall impact of a shock in j on all other variables.

$$TO_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \quad (4)$$

Equation 5 (***Total Directional Connectedness from Others - FROM***): represents the cumulative effect of all other variables on the *j* variable.

$$\mathrm{FROM}_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) \quad (5)$$

Equation 6 (***Net Total Directional Connectedness - NET***): allows us to decide whether a variable is a net shock transmitter or receiver by subtracting the effect of variable *j* on others from the effect of others on variable *j*. If $NET > 0$, it means that variable *j* has a greater impact on the other variables in the network than the other variables have on variable *j*. This implies that variable *j* is a net transmitter of shocks and drives the network. On the other hand, if $NET < 0$, other variables in the network have a greater impact on variable *j* than otherwise. This implies that variable *j* is a net receiver of shocks and is driven by the network.

$$NET_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) - \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) = TO_{jt} - FROM_{jt} \quad (6)$$

Equation 7 (***Total Connectedness Index – TCI***): is a measure used to calculate a network's overall connectedness in both static and dynamic structures. A relatively high TCI value indicates that the network is significantly interconnected, meaning that most nodes in the network are connected to multiple other nodes. This implies that the variables in the network are highly dependent on each other and that a shock or change in one variable will likely affect the other variables in the network.

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt} \quad (7)$$

Equation 8 (***Net Pairwise Directional Connectedness - NPDC***): provides information about the bilateral relationship between $j$ and $i$ via subtracting the impact variable $j$ has on variable $i$ by the influencing variable $i$ has on variable *j*. If $NPDC_{ijt} > 0$ ($NPDC_{ij,t} < 0$), it means that the variable *j* dominates (*is dominated by*) the variable *i*.

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}^{g}(H) - \tilde{\phi}_{ji,t}^{g}(H) \quad (8)$$

## 3. EMPIRICAL FINDINGS

We set the TVP-VAR forgetting factor as 0.99 and the EWMA forgetting factor as 0.97 by following Antonakakis et al. (2020) since the fixed values shrank the computation burden of the Kalman filter algorithm significantly and these decay factors show the minimum error in simulations. Table 3 presents the output of the total connectedness index (TCI) derived from the TVP-VAR(1) model with the Minessota

**Table 3:** Total connectedness index

| | AMZN | BABA | PDD | JD | MELI | SHOP | CPRT | SEA | EBAY | ETSY | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **AMZN** | 32.44 | 7.87 | 4.87 | 7.33 | 10.21 | 11.75 | 5.3 | 6.14 | 6.66 | 7.41 | 67.56 |
| **BABA** | 10.15 | 35.88 | 9.86 | 13.94 | 5.76 | 7.36 | 2.96 | 5.51 | 3.8 | 4.78 | 64.12 |
| **PDD** | 8.26 | 12.91 | 39.66 | 11.94 | 4.52 | 6.11 | 2.18 | 6.49 | 3.06 | 4.86 | 60.34 |
| **JD** | 8.92 | 15.85 | 8.68 | 34.98 | 7.43 | 5.93 | 3.81 | 6.25 | 3.31 | 4.85 | 65.02 |
| **MELI** | 13.16 | 6.69 | 4.45 | 6.58 | 30.69 | 10.79 | 5.65 | 7.43 | 5.48 | 9.06 | 69.31 |
| **SHOP** | 14.04 | 7.48 | 4.91 | 6.58 | 11.57 | 30.68 | 4.21 | 7.61 | 4.77 | 8.13 | 69.32 |
| **CPRT** | 9.45 | 5.84 | 4.18 | 6.74 | 9.27 | 8.36 | 38.16 | 5.38 | 5.82 | 6.79 | 61.84 |
| **SEA** | 10.42 | 7.63 | 6.15 | 7.23 | 9.48 | 9.65 | 3.44 | 32.63 | 4.76 | 8.61 | 67.37 |
| **EBAY** | 11.4 | 5.23 | 4.26 | 5.22 | 8.46 | 7.73 | 5.78 | 5.99 | 38.03 | 7.88 | 61.97 |
| **ETSY** | 11.64 | 6 | 4.27 | 6.24 | 10.64 | 9.93 | 4.87 | 7.79 | 6.24 | 32.39 | 67.61 |
| **TO** | 97.45 | 75.49 | 51.65 | 71.82 | 77.35 | 77.61 | 38.2 | 58.61 | 43.91 | 62.38 | 654.46 |
| **Inc.Own** | 129.89 | 111.37 | 91.31 | 106.8 | 108.04 | 108.29 | 76.36 | 91.24 | 81.94 | 94.77 | **TCI** |
| **NET** | **29.89** | **11.37** | **-8.69** | **6.8** | **8.04** | **8.29** | **-23.64** | **-8.76** | **-18.06** | **-5.23** | 65.45 |
| **NPT** | 9 | 8 | 2 | 6 | 7 | 5 | 0 | 3 | 1 | 4 | |

*Notes:* Results are based on a TVP-VAR model with a lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition. Estimation is done using the R software program and the package "ConnectednessApproach" by Gabauer (2022). Inc.Own: Including own contributions.

*Source:* Authors' own calculation

Prior[3] through GFEVD with a forecast horizon of 10 days. In other words, the table below shows the volatility connectedness between the range-based volatility of e-commerce companies' stock prices.

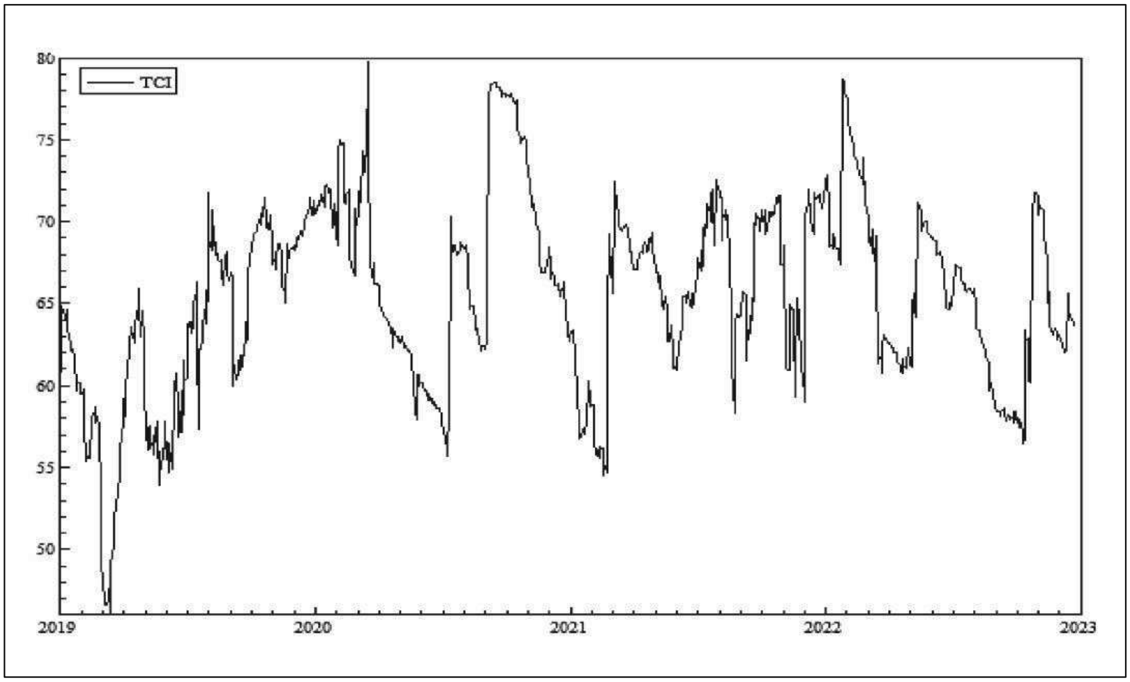
### 3.1 Average Connectedness Results

TCI shows that the forecasting error variance in the variables is due to the transition and connectedness between these variables, being relatively high. While the diagonal elements of the 10×10 matrix evident in Table 3 illustrate the forecasting error variance caused by the variables themselves, the other elements are the decomposition of the error variances. The diagonal elements unveil self-inflicting volatility spillovers while all the off-diagonal elements portray spillover rates.

We may express that the ijth entry of the matrix is the estimated contribution to the forecast error variance of stock i emanating from disturbances to stock j. The columns "TO" show the variance decompositions of spillover to other variables, while the row elements "FROM" depict the shocks from other variables. One can calculate the average net directional connectedness "NET" via Equation 6. Accordingly, we

[3] Sice the TVP-VAR model is estimated using a Bayesian approach, prior knowledge is required. Antonakakis et al. (2020) performed a prior sensitivity analysis using a non-informative, informative, and randomly selected 500 Minnesota priors. Findings associated with the Prior sensitivity analysis showed that the prior effect was negligible after the coefficients were updated approximately 50 times.

**Figure 2:** Dynamic total connectedness



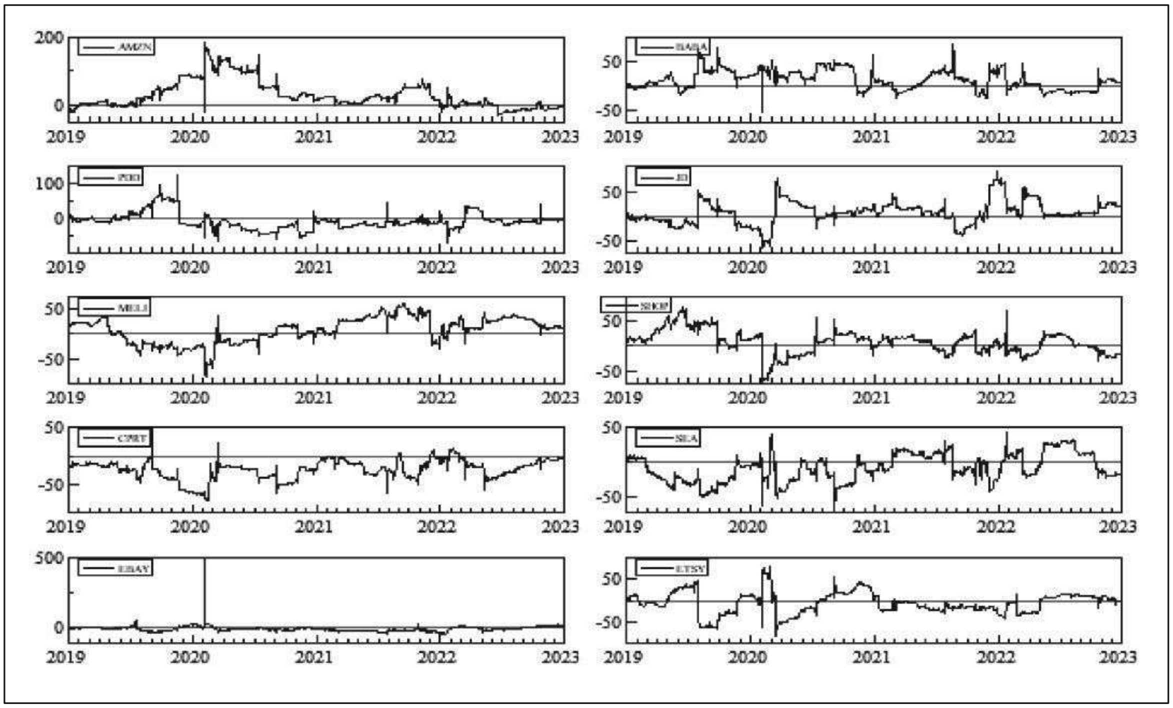

Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition. Source: Authors' own calculation.

understand that AMZN, BABA, JD, MELI, and SHOP are net shock transmitters while other stocks are shock receivers. A closer look at Table 3 allows for a distinction of network variables between net transmitters and net receivers of uncertainty shocks. In this context, it becomes quite clear that AMZN is the largest net receiver in the network with an average net connectedness value of 29.89% whereas CPRT is the main average net receiver of the network with an average value of -23.64%. The weakness of the average results is that although it provides a general picture of the connectedness between the variables of the network, it, unfortunately, does not reveal a dynamic examination of the connectedness between the variables by dividing the sample period into shorter intervals. And that is because average results can mask major economic developments and events that occurred during the sampling period that had a profound impact on the network under study (Chatziantoniou et al., 2022). Hence, we examine the dynamic structure of the network in the following subsections.

## 3.2 Dynamic Total Connectedness

It is acknowledged that dynamic TCI is assumed as a robustness check for the analysis. The dynamic TCIs in Figure 2 vary with time. It is one of the first striking results that the change has increased significantly during the pandemic period. The increase in dynamic TCI in late December 2019, when the COVID-19 epidemic started, and in March 2020, when the World Health Organization (WHO) officially declared COVID-19 as a pandemic, is remarkable. Already, the total TCI on the network reached its highest value of 79.73% on March 16, 2020, shortly after the pandemic was declared on March 11, 2020. The reduction of pandemic restrictions and the resumption of production and supply chain activities at the beginning of summer 2020 had a positive impact on the stock prices of retail e-commerce companies. And that increased the TCI level by 78.5% in September 2020. Also, another remarkable peak is seen at the end of January 2022 at the level of 78.31% TCI. This period coincides with the dates when the tensions between Russia and Ukraine started to mount. On February 24, 2022, when the

**Figure 3:** Dynamic net total directional connectedness




Source: Authors' own calculation.

war started, the shock effect experienced in the markets also affected e-commerce companies' stock volatility and the volatility spillover was realized as 73.90% on average (see Ari, 2022b). In December 2022, it is understood that the average TCI of the network increased, especially with the sharp decrease in AMZN stock prices. AMZN stock price is down 49.7% from December 31, 2021, the lowest closing level since March 12, 2019. The reason is that high inflation in Western countries has led to significant price increases for goods and services, prompting central banks to raise interest rates. This, coupled with the economic slowdown, is believed to potentially trigger a recession as consumers become cautious, prioritizing essential purchases and nullifying gains made by e-commerce companies during the COVID-19 crisis.

The Federal Reserve changed the target federal funds rate seven times in 2022. In an attempt to respond to the COVID-19 health emergency and the accompanying economic downturn, the Fed lowered the federal funds rate to nearly zero and implemented quantitative easing (QE) to support the economy. However, as the economy began to rebound and inflationary pressures increased, the Fed took a hawkish policy stance by raising the federal funds rate to contain inflation and prevent it from spiraling out of control. Thereafter, on March 17, 2022, it increased interest rates by 25 basis points to 0.50%. Finally, on 14 December 2022, it increased the benchmark interest rate to 4.50%. The declines experienced in the stock markets during these dates also appear in our dynamic total connectedness index. Because, according to the connectedness theory, the TCI index is expected to rise especially in times of crisis, and our results validate this. In addition, the fact that inflation values were higher than expected all over the world in 2022 caused decreases in the markets. Equity markets, for instance, fell sharply on the afternoon of May 11, 2022. The increase in TCI from 64.58% to 70.90% on May 12, 2022, indicates the effect of the negative mood in the market.

## 3.3 Dynamic Net Total Direct Connectedness

Volatility transmitters and receivers can be identified by using measures such as Net Total Directional Connectedness (hereinafter NET).

**Table 4:** Average net pairwise directional connectedness index

| | BABA | PDD | JD | MELI | SHOP | CPRT | SEA | EBAY | ETSY |
|---|---|---|---|---|---|---|---|---|---|
| **AMZN** | 2.283 | 3.391 | 1.585 | 2.950 | 2.292 | 4.145 | 4.276 | 4.740 | 4.227 |
| **BABA** | | 3.046 | 1.908 | 0.927 | 0.121 | 2.885 | 2.119 | 1.430 | 1.221 |
| **PDD** | | | -3.259 | -0.073 | -1.193 | 2.000 | -0.337 | 1.202 | -0.593 |
| **JD** | | | | -0.842 | 0.657 | 2.932 | 0.985 | 1.913 | 1.387 |
| **MELI** | | | | | 0.779 | 3.620 | 2.043 | 2.981 | 1.578 |
| **SHOP** | | | | | | 4.149 | 2.039 | 2.961 | 1.796 |
| **CPRT** | | | | | | | -1.948 | -0.039 | -1.926 |
| **SEA** | | | | | | | | 1.236 | -0.821 |
| **EBAY** | | | | | | | | | -1.635 |

Source: Authors' own calculation.

Once identified, both volatility transmitters and receivers can be closely monitored and regulated to reduce the risk of contagion effects in a financial network. Unlike the average NET values, Figure 3 shows us the dynamic results that reveal in which periods e-commerce companies are transmitters or receivers of volatility.

AMZN appears to be a volatility transmitter for almost the entire period. Nonetheless, in early 2022, high inflationary pressures, supply chain restrictions, and the armed conflict in Ukraine put more strain on Amazon and other e-commerce companies. In addition, e-commerce giant AMZN completed its 20-to-1 share split on June 6, 2022, and its shares traded below $1,000 for the first time since 2017. This decline continued until the end of 2022. For these reasons, AMZN turns out to be the volatility receiver after June 2022. Another interesting finding is that we see that CPRT and EBAY are receivers of volatility throughout the entire period. In early February 2020, Intercontinental Exchange Inc, the owner of the NYSE, reported that it was exploring several potential opportunities to acquire the e-commerce company EBAY. However, they announced that they have not contacted EBAY and are not negotiating to sell all or part of the company. NET values show that the shock waves of these rumors have made EBAY a volatility transmitter, even for a short period. EBAY's average NET index value rose to 496.93% at the beginning of February 2020.

### 3.4 Pairwise Interconnectedness

The NPT numbers in Table 3 evidence that the most dominant company in the network is AMZN, dominating the other nine companies as a volatility transmitter. Table 4 shows the average Net Pairwise Directional Connectedness (NPDC, hereinafter) index. AMZN transmits the most volatility to EBAY by 4.74%. The sum of the net pairwise connectedness values equals the NET values. It is seen that the second dominant stock in terms of volatility transmission is BABA.

Since the NPDC fell short of demonstrating the strength of bilateral interconnectedness, Gabauer (2021) decomposed TCI and developed a Pairwise Connectedness Index (PCI). The TCI is a measure of the overall interconnectedness of a system while the PCI measures the interconnectedness between specific pairs of variables within the system. The PCI ranges between 0 and 1 with a value of 1 indicating a strong connection between the two variables and a value of 0 indicating no connection. The PCI values shown in Table 5 demonstrate that the stron-

**Table 5.** average pairwise connectedness index (PCI)

| | BABA | PDD | JD | MELI | SHOP | CPRT | SEA | EBAY | ETSY |
|---|---|---|---|---|---|---|---|---|---|
| **AMZN** | 41.518 | 30.718 | 38.981 | 54.797 | 58.218 | 36.049 | 41.255 | 41.601 | 45.956 |
| **BABA** | | 47.057 | 59.491 | 32.545 | 36.724 | 22.538 | 34.130 | 23.082 | 28.733 |
| **PDD** | | | 42.719 | 23.755 | 27.377 | 16.382 | 31.562 | 17.917 | 23.836 |
| **JD** | | | | 36.573 | 32.955 | 26.618 | 35.425 | 22.125 | 29.775 |
| **MELI** | | | | | 53.766 | 36.289 | 43.199 | 34.417 | 48.715 |
| **SHOP** | | | | | | 31.445 | 43.747 | 30.957 | 45.304 |
| **CPRT** | | | | | | | 23.235 | 27.099 | 28.782 |
| **SEA** | | | | | | | | 27.511 | 42.382 |
| **EBAY** | | | | | | | | | 34.469 |

Source: Authors' own calculation.

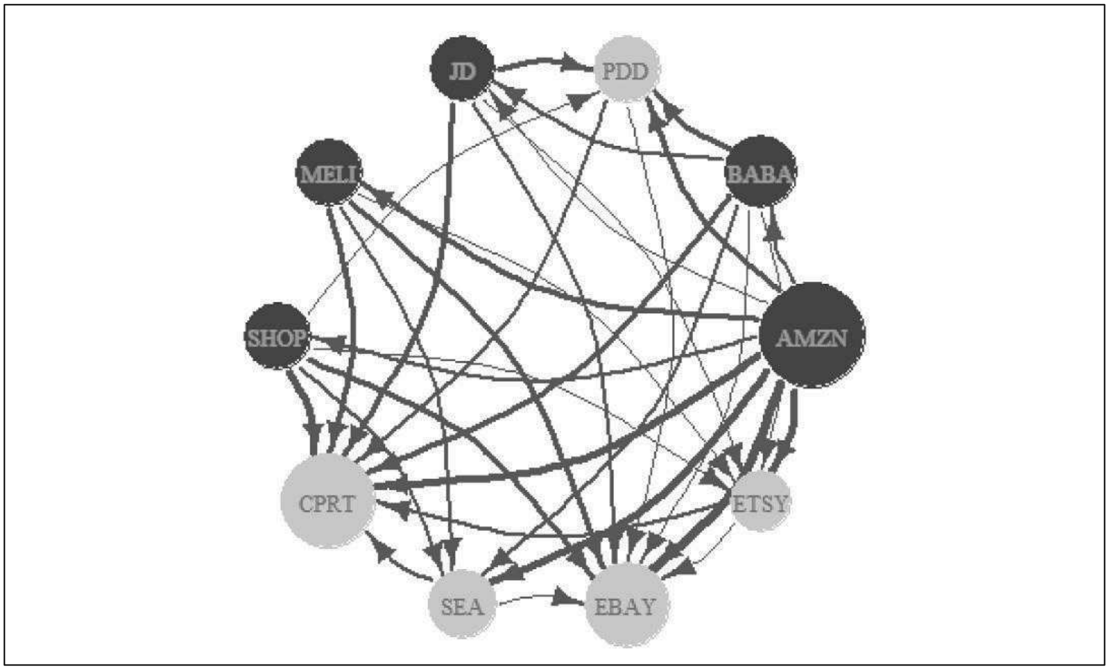
gest bilateral interconnectedness transpires between BABA and JD by 59.49%. Bilateral volatility interconnectedness is expected to be high, especially among companies from the same region, which is exactly the case herein.

Another method to support pairwise connectedness is network plots as illustrated in Figure 4. A network plot in a TVP-VAR based connectedness analysis is a graphical representation of the dynamic relationships between the variables. It is used to visualize the strength and direction of the causal links between the variables over time. The plot typically shows the variables as nodes in a network with lines connecting them to indicate the presence and strength of a causal relationship. The lines are weighted to indicate the strength of the relationship and are directed to indicate the direction of causality. Additionally, the color of the edges can indicate the sign of the relationship. It can be used to identify the key drivers of the system over time as well as any potential feedback loops or other complex interactions between variables. The color of a node in a network can show whether it transmits or receives net returns/volatility, with darker colors indicating stronger effects on other nodes. The dark nodes in Figure 4 indicate volatility transmitters and the light ones indicate volatility receivers.

## 4. CONCLUSION

We examine the dynamic volatility connectedness predicated upon the Diebold-Yilmaz method, which is particularly useful for analyzing high-frequency financial data, as it allows for the detection of changes in volatility and volatility spillovers over time. Accordingly, we can obtain an estimate of the degree of connectedness between the volatilities of different e-commerce companies, and how that degree of connectedness varies over time. For that purpose, we implement the TVP-VAR Connectedness approach to reveal the dynamic structure of volatilities between the stock prices of e-commerce companies. By analyzing the daily log-return data of the largest e-commerce companies by market capitalization and obtaining the volatility of stocks using the Garman and Klass range-based approach, we can gain insight into the interconnectedness of the volatilities of these companies. This can help us understand how changes in one company's stock price can affect the stock prices of other companies in the e-commerce market. Our findings suggest that the volatility connectedness between e-commerce companies' stock prices is relatively high and that the most dominant stock in the network is Amazon. The results also portray that the strongest bilateral volatility interconnectedness is between the

**Figure 4:** Network plot




Source: Authors' own calculation

stocks of Alibaba and Jingdong Mall. Additionally, the change in the TCI index increased significantly during the pandemic period, reaching its highest value in March 2020. The reduction of pandemic restrictions and the resumption of production and supply chain activities at the beginning of summer 2020 had a positive impact on the stock prices of retail e-commerce companies. Another remarkable peak is seen at the end of January 2022, coinciding with the dates when the tensions between Moscow and Kyiv started to increase. The war that erupted on February 24, 2022, also affected e-commerce companies' stock volatility, and the volatility spillover was realized as 73.90% on average. Moreover, the TCI index is expected to rise especially in tumultuous times, and this was validated by the results. Finally, the fact that inflation values were higher than expected all over the world in 2022 caused decreases in the markets, and that is fully reflected in the increases in the TCI index.

The analysis of NPDC values elucidates that AMZN and BABA stocks function as principal nodes within the network, effectively acting as the most significant risk transmitters. This dominance suggests a strategic portfolio construction approach where these stocks are not conglomerated within a singular investment basket. Specifically, the aggregation of CPRT, SEA, EBAY, and ETSY stocks, which exhibit a heightened risk transmission from AMZN, could potentially exacerbate financial losses during periods of economic instability.

Furthermore, the NPDC index identifies pairs such as PDD and MEL, BABA and SHOP, and CPRT and EBAYas exhibiting negligible interconnectivity. This characteristic renders them as viable candidates for inclusion within the same investment portfolio due to their relative independence.

Additionally, the assessment of Average PCI values provides insights into the intensity of bilateral volatility connectedness among stocks. The pairs AMZN-MELI, AMZN-SHOP, and AMZN-ETSY, distinguished by their robust connectivity as per their PCI values, are preferably excluded from being paired in a single investment portfolio to mitigate enhanced risk transmission. This principle is similarly applicable to the BABA-PDD and BABA-JD pairs. Conversely, for enhancing portfolio diversification, pairs exhibiting weak connections, such as PDD-MELI and CPRT-EBAY, can be strategically considered for portfolio inclusion due to their weak interconnectivity.

Despite Meituan, JD Health, Coupang, and Chewy being among the largest companies in terms of market value, their initial listing dates on international stock exchanges coinciding with the period post the onset of the Covid-19 pandemic necessitates their exclusion from this study, a limitation to be acknowledged. Furthermore, the decision to commence the data period on January 2, 2019, is another constraint, chosen to reduce data loss.

In future research, it would be beneficial to increase the number of firms within the network. This could potentially reveal the influence of companies with smaller market shares on stock return risks in larger firms. Moreover, by analyzing risk transmissibility via connectedness indices, more comprehensive results can be attained in portfolio selection contexts.

While it appears implausible to extend the data period for the stocks included in our study, it is believed that outcomes that may emerge over a longer period would not significantly impact the results obtained. We do not anticipate changes in the characteristic risk structures of the stocks or their dominance throughout the period. This is based on the observation that the risk transmissibility structures of market-dominant companies display similarities in both normal market conditions and during crisis periods.

Additionally, the application of the frequency connectedness method is instrumental in uncovering indices of connectivity for both short-term and long-term periods. This approach facilitates a comprehensive understanding of the network's risk transitivity across these varying timeframes. Furthermore, employing the Quantile-VAR model is beneficial for contrasting the median-based connectedness with the tail connectedness within the network, offering a nuanced perspective on its structural dynamics.

All in all, our findings support that the most important factors affecting the volatility connectedness among e-commerce companies are the beginning of the Covid-19 global health emergency, the reduction of pandemic-related restrictions and the increase in demand, the onset of the Russo-Ukrainian conflict, high inflation in developed markets and the corresponding policy rate hikes. These factors have a significant impact on the stock prices of e-commerce companies and the interconnectedness of their volatilities. Eventually, the findings demonstrate the impact of global events on the e-commerce market and how these events can shape market dynamics.

## References

Adekoya, O. B., Oliyide, J. A., Yaya, O. S., & Al-Faryan, M. A. S. (2022). Does oil connect differently with prominent assets during war? Analysis of intra-day data during the Russia-Ukraine saga. *Resources Policy*, *77*, 102728.

Alam, M. K., Tabash, M. I., Billah, M., Kumar, S., & Anagreh, S. (2022). The impacts of the Russia–Ukraine invasion on global markets and commodities: a dynamic connectedness among G7 and BRIC markets. *Journal of Risk and Financial Management*, *15*(8), 352.

Anscombe, F. J., & Glynn, W. J. (1983). Distribution of the kurtosis statistic b 2 for normal samples. *Biometrika*, *70*(1), 227-234.

Antonakakis, N., & Gabauer, D. (2017). Refined measures of dynamic connectedness based on TVP-VAR.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), 84.

Antonakakis, N., Gabauer, D., Gupta, R., & Plakandaras, V. (2018). Dynamic connectedness of uncertainty across developed economies: A time-varying approach. *Economics Letters*, *166*, 63-75.

Ari, Y. (2022a). The comparison of range-based volatility estimators and an application of TVP-VAR-based connectedness. *Journal of Life Economics*, *9*(3), 147-157.

Ari, Y. (2022b). TVP-VAR based CARR-volatility connectedness: Evidence from the Russian-Ukraine conflict. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 7(3), 590-607.

Balcilar, M., Gabauer, D., & Umar, Z. (2021). Crude Oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. *Resources Policy*, *73*, 102219.

Bissoondoyal-Bheenick, E., Do, H., Hu, X., & Zhong, A. (2021). Learning from SARS: Return and volatility connectedness in COVID-19. *Finance Research Letters*, *41*, 101796.

Bouri, E., Cepni, O., Gabauer, D., & Gupta, R. (2021). Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis*, *73*, 101646.

Cagli, E. C., Mandaci, P. E., & Taskin, D. (2023). The volatility connectedness between agricultural commodity and agri businesses: Evidence from time-varying extended joint approach. *Finance Research Letters*, *52*, 103555.

Chatziantoniou, I., Gabauer, D., & Marfatia, H. A. (2022). Dynamic connectedness and spillovers across sectors: Evidence from the Indian stock market. *Scottish Journal of Political Economy*, *69*(3), 283-300.

Chirilă, V. (2022). Connectedness between Sectors: The Case of the Polish Stock Market before and during COVID-19. *Journal of Risk and Financial Management*, *15*(8), 322.

Costa, A., Matos, P., & da Silva, C. (2022). Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics. *Finance Research Letters*, *45*, 102124.

COVID-19 Boost to e-Commerce Sustained into 2021, New UNCTAD Figures Show | UNCTAD Available online: https://unctad.org/news/covid-19-boost-e-commerce-sustained-2021-new-unctad-figures-show (accessed on 26 January 2023).

D'Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. *Biometrika*, 679-681.

Dhanapal, S., Vashu, D., & Subramaniam, T. (2015). Perceptions on the challenges of online purchasing: a study from "baby boomers", generation "X" and generation "Y" point of views. *Contaduría y administración*, *60*, 107-132.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158-171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119-134.

Diebold, F. X., & Yilmaz, K. (2015). Trans-Atlantic equity volatility connectedness: US and European financial institutions, 2004–2014. *Journal of Financial Econometrics*, *14*(1), 81-127.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1992). Efficient tests for an autoregressive unit root.

Fisher, T. J., & Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association*, *107*(498), 777-787.

Gabauer, D. (2021). Dynamic measures of asymmetric & pairwise connectedness within an optimal currency area: Evidence from the ERM I system. *Journal of Multinational Financial Management*, *60*, 100680.

Gabauer, D. (2022). Connectednessapproach: connectedness approach. *R package version*, *1*(1).

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of Business*, 67-78.

Global E-Commerce Share of Retail Sales 2026 Available online: https://www.statista.com/statistics/534123/e-commerce-share-of-retail-sales-worldwide/ (accessed on 26 January 2023).

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255-259.

Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, *71*, 101-116.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of econometrics, 74(1), 119-147.

Korobilis, D., & Yilmaz, K. (2018). Measuring dynamic connectedness with large Bayesian VAR models. *Available at SSRN 3099725*.

Nasreen, S., Tiwari, A. K., & Yoon, S. M. (2021). Dynamic connectedness and portfolio diversification during the coronavirus disease 2019 pandemic: Evidence from the cryptocurrency market. *Sustainability*, *13*(14), 7672.

News, B. Amazon Deepens Gloom for Battered E-Commerce Stocks - BNN Bloomberg Available online: https://www.bnnbloomberg.ca/amazon-deepens-gloom-for-battered-e-commerce-stocks-1.1759880 (accessed on 26 January 2023).

Nguyen, M. H., Armoogum, J., & Nguyen Thi, B. (2021). Factors affecting the growth of e-shopping over the covid-19 era in hanoi, vietnam. *Sustainability*, *13*(16), 9205.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17-29.

Rosário, A., & Raimundo, R. (2021). Consumer marketing strategy and E-commerce in the last decade: a literature review. *Journal Of Theoretical and Applied Electronic Commerce Research*, *16*(7), 3003-3024.

Shahzad, U., Mohammed, K. S., Tiwari, S., Nakonieczny, J., & Nesterowicz, R. (2023). Connectedness between geopolitical risk, financial instability indices and precious metals markets: Novel findings from Russia Ukraine conflict perspective. *Resources Policy*, *80*, 103190.

Shaw, N., Eschenbrenner, B., & Baier, D. (2022). Online shopping continuance after COVID-19: A comparison of Canada, Germany and the United States. *Journal of Retailing and Consumer Services*, *69*, 103100.

Umar, Z., Jareño, F., & Escribano, A. (2023). Analysis of the dynamic return and volatility connectedness for non-ferrous industrial metals during the COVID-19 pandemic crisis. *Studies in Economics and Finance*, *40*(2), 313-333.

Yakup, ARI. (2022). TVP-VAR Based CARR-Volatility Connectedness: Evidence from The Russian-Ukraine Conflict. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, *7*(3), 590-607.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of econometrics, 74(1), 119-147.

## Povezanost volatilnosti među globalnim dionicama e-trgovine

**Sažetak**

*Ovaj rad proučava povezanost volatilnosti između cijena dionica e-trgovinskih poduzeća. U tu svrhu implementira se TVP-VAR-Based postupak povezanosti kako bi se otkrila dinamička struktura volatilnosti. Ovaj pristup pomaže utvrditi prijenos volatilnosti između imovine koja prima ili prenosi rizik. Pritom se koriste logaritamski vrijednosti dnevnih povrata najvećih e-trgovinskih poduzeća prema tržišnoj kapitalizaciji. Skup podataka sastoji se od dnevnih cijena otvaranja, zatvaranja, najviših i najnižih cijena dionica u razdoblju od 2019-01-02 do 2022-12-23. Volatilnost dionica dobivena je koristeći Garman-Klass pristup temeljen na rasponu. Rezultati pokazuju da je prosječni ukupni indeks povezanosti relativno visok sa 65,45%, što znači da je varijanca prognostičke pogreške u varijablama rezultat prijenosa i povezanosti između tih varijabli. Nadalje, rezultati dvosmjerne povezanosti pokazuju da je Amazon najdominantnija dionica unutar mreže. Na kraju, otkrivamo da se najjača bilateralna povezanost volatilnosti javlja između dionica Alibabe i Jingdong Mall-a.*

**Ključne riječi:** E-trgovina, Diebold-Yılmaz povezanost, Garman-Klass volatilnost, TVP-VAR