Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Exchange rate volatility connectedness during Covid-19 outbreak: DECO-GARCH and Transfer Entropy approaches

Ngo Thai Hung, Linh Thi My Nguyen, Xuan Vinh Vo

A R T I C L E   I N F O

JEL classification:
F31
G15
C32

Keywords:
Exchange rate
Covid-19 outbreak
DECO
Transfer entropy

A B S T R A C T

Motivated by the severe impacts of the Covid-19 outbreak on the global trade and capital flows, which can shift the forex market structure, this paper aims to examine the equicorrelation and causal association across major currency markets during Covid-19 pandemic using novel approaches: DECO-GARCH and Transfer Entropy. We find that major exchange rate markets have a positive equicorrelation, and these trends have been more pronounced during the Covid-19 crisis, uncovering the existence of contagion effects. The results also show the causal associations between the currency markets, depicted by three categories: no effect, mono-direction, and bi-direction. Such connections unveil the shock sender and receiver in the examined exchange rate markets, supporting that there is contagion risk across currency markets. Our findings suggest important implications for investors, firms, and policymakers in risk management during crisis periods.

1. Introduction

The paper examines the equicorrelation and causal association among the most actively traded exchange rates during the Covid-19 pandemic using two novel approaches: DECO-GARCH and Transfer Entropy. The exchange rate is considered a crucial channel to connect various economies (Wan & He 2021). Exchange rate stability is also among the main concerns of policymakers due to its strong link with national trade balance, capital flows, and foreign debts (Padhan & Prabheesh 2021).

Our study is motivated by two main reasons. The first reason is the abnormal contagion and spillover effects documented in various financial markets during crisis periods (van Horen et al. 2006; Coudert et al. 2011; Baur 2012; Ranta 2013; Banerjee 2021; Wang et al. 2021). Secondly, the paper is motivated by the severe and unique impacts of the ongoing Covid-19 outbreak on international trade and capital flows which might change the exchange rate structure and challenge prior research findings.

Although exchange rate volatility transmission can be normal in today’s globalized financial markets, it may become abnormal during crises, reflecting the “contagion effects” in these turmoil periods (Coudert et al. 2011). For example, Coudert et al. (2011) investigate exchange rate volatility in 21 emerging markets across several financial crises (1994–2009) and show supporting evidence for the contagion effects (regional) from one developed market to other emerging markets. Similarly, in a recent study, Wen and Wang (2020) examine the linkages of 65 major currencies (2000–2019) and find that currency volatility connectedness increases with financial crises.
The Covid-19 outbreak is often referred to as a unique crisis that profoundly impacts many countries (Kulic et al. 2021). It is even considered the most severe crisis after World War II, affecting more than 50 million people in almost all nations (OECD 2020c). The severe impacts and distinct features of the Covid-19 pandemic might change the exchange rate structure and challenge prior research findings on exchange rate volatility and volatility connectedness. Remarkably, the outbreak has triggered strict social distancing and lockdown restrictions across many cities/countries worldwide to reduce the virus spread, and thus drastically disrupted the international trade network and capital flows (Vidya & Prabheesh 2020). Vidya and Prabheesh (2020) report that the outbreak leads to a dramatic drop in trade connectedness among top economies and a “visible change” in the trade network structure. Indeed, statistics show that global trade could drop by 12% to 32% (WTO 2020), and FDI flows could also decrease by approximately 40% in 2020 (OECD 2020b). Many emerging and developed countries are even reported to stop their cross-border portfolio investments in March 2020 (OECD 2020c).

Given its overwhelming impacts on the global economy, many studies have found supporting evidence for the adverse effects of the Covid-19 outbreak on the macroeconomy (e.g., GDP growth, employment, supply chain…) (e.g., Qin et al. 2020; Vidya & Prabheesh; Yang & Vo 2020), the stock market (e.g., Liu et al. 2020), commodity market (e.g., Hung & Vo 2021), and exchange rate return and volatility (e.g., Narayan et al. 2020; Njindan Iyke 2020; Feng et al. 2021). However, little research has attempted to investigate the dynamic exchange rate connectedness among major currencies during the outbreak. In this context, our paper is the first to examine the dynamic equicorrelation and causal association of six widely traded currencies, including EURO, CAD, GBP, AUD, CHF, and JPY (Barunik et al. 2017), during the Covid-19 pandemic under two new approaches: DECO-GARCH and Transfer Entropy. We examine the daily exchange rates of the six currency pairs concerning the US dollar because USD is a dominant currency in international markets even during market structure shifts (BIS 2020).

Our study contributes to the related literature in several primary ways. First, it looks into the evolution of the dynamic equicorrelation between the six major exchange rate markets during the Covid-19 pandemic, providing deeper insights into risk hedging and diversification opportunities during turbulent periods. This is important to the current literature, given the potential structural shifts in the forex markets triggered by the adverse effects of the pandemic on international trade and capital flows. We find supporting evidence for excessive volatility, which can be driven by the uncertain economic circumstances and negative market sentiment during the Covid-19 outbreak. Given that exchange rate stability is an essential target of policymakers due to its profound impact on the trade balance, capital flows, and foreign debts (Padhan & Prabheesh 2021), our findings are thus beneficial for regulators in making/adjusting relevant policies as well as surveillance mechanisms. Moreover, we uncover significant contagion and spillover effects among the main exchange rates during the pandemic. Exchange rate volatility spillover is a crucial issue in the literature due to its implications for portfolio diversification/management and risk hedging strategy (Jayasinghe & Tsui 2008; Aboura & Chevallier 2014; Barunik et al. 2017).

Second, we add to the body of knowledge by combining a DECO-GARCH specification with the frameworks of Ling and McAleer (2002) and Engle and Kelly (2012) to investigate conditional spillover effects among exchange rate markets. The dynamic equicorrelation class of correlation models attempts to solve the computational difficulties of dynamic conditional correlation problems (Mensi et al. 2020; Hung 2021). The DECO model generates a single dynamic correlation coefficient that measures the degree of exchange rate return correlation (Demiralay & Golitsis 2021). As a result, instead of investigating each pair-wise correlation to study market co-movements, we can employ the DECO model to examine the market integration of the most considerable exchange rates by a number (Hung 2020; Demiralay & Golitsis 2021). Recently, several works, including Menşi et al. (2020), Umar et al. (2019), Cai et al. (2016), and Hung (2021), explore the dynamic co-movements in various financial markets using the multivariate DECO-GARCH approach. Nevertheless, little research has been conducted on the exchange rate markets. Addressing the gap, we employ a single dynamic equicorrelation coefficient to investigate market integration and convergence or divergence of the world’s major exchange rates during the Covid-19 crisis.

Third, we quantify the information flows between major exchange rates by employing the Transfer Entropy approach by Shannon (1948). The method has been used by several studies to examine the relationships between financial data (for example, Huynh 2020; Huynh et al. 2020; Dimpf and Peter 2013). The Transfer Entropy approach is different from the popular spillover indices used in prior studies (e.g., Diebold and Yilmaz 2012; Barunik and Krehlík 2018), which tend to overlook the intrinsic information underlying market movements (Owusu Junior et al. 2021). Thus, utilizing the ‘Transfer Entropy approach can shed more light on the global currency market integrations’ information flows and causality levels, which is critical for policymakers and investors.

The remainder of our paper is structured as follows. Section 2 reviews relevant literature about exchange rate volatility and volatility connectedness. Section 3 describes the study sample and testing methods. The main results are presented in Section 4. Lastly, Section 5 discusses the main findings and concludes our study.

2. Literature review

A review of relevant literature shows three main strands of research on exchange rate volatility. The first strand of literature focuses on factors affecting exchange rate volatility across different countries (Kanas 2002; Stancik 2007; Kroli 2014; Al-Abri & Baghestani 2015). For example, Kanas (2002) studies the relationship between home stock return volatility and the volatility of exchange rates in the US, the UK, and Japan and reports that stock return volatility significantly affects exchange rate volatility. Stancik (2007) investigates determinants of new EU members’ exchange rate volatility and shows that economic openness, news, and flexible regimes affect exchange rate volatility. However, the relationships vary across different members. In Asia, Al-Abri and Baghestani (2015) find that foreign investment significantly affects real exchange rate volatility in eight emerging markets in Asia. Kroli (2014) examines the influence of general economic and economic policy uncertainty on exchange rate volatility of various countries (Canada, the UK,
Japan, Brazil, Mexico, South Korea, Sweden, India, South Africa, EU area) and finds supporting evidence for their positive relationship.

The second strand of research investigates the impacts of exchange rate volatility on critical economic indicators (e.g., Dang et al., 2020; Latief and Lefen, 2018; Lizardo, 2009; Thuy and Thuy, 2019). This literature strand shows that most studies find a negative influence of exchange rate volatility on macroeconomic factors in different contexts. For example, exchange rate volatility negatively influences trade (Lizardo 2009) (across 28 Latin American and Caribbean markets). Latief and Lefen (2018) investigate the impact of exchange rate volatility on foreign direct investment and international trade in India, Sri Lanka, Bangladesh, Bhutan, Pakistan, Maldives, and Nepal and find a consistently negative impact. Lyke and Ho (2018) also show a negative effect of exchange rate volatility on domestic consumption (Ghana). Similarly, exchange rate volatility is found to adversely impact exports (Thuy & Thuy 2019) (Vietnam).

The third strand of literature studies the volatility connectedness and/or transmission/spillover effects between (1) the forex market and other markets such as stock and commodity markets (e.g., Kalu et al., 2020; Kumar et al., 2019; Mensi et al., 2021) and (2) various forex markets which are in line with our current research (e.g., McMillan & Speight 2010; Greenwood-Nimmo et al. 2016; Barunik et al. 2017; Bouri et al. 2020; Wen & Wang 2020). Regarding the former line of research, studies have shown significant links between exchange rates and other assets. Kumar et al. (2019) find supporting evidence for dependence between stock and forex markets in the BRICS region in various market conditions using a dependence-switching copula model. Similarly, Mensi et al. (2021) show significant spillover effects of precious metals (silver, palladium, and platinum) on major currencies such as AUD, CAD (most significant spillovers), and JPY, CNY (smallest spillovers). They also reveal that the spillovers tend to increase with more financial and economic uncertainty.

Building on the latter strand of literature on exchange rate volatility spillovers, initiated by the pioneering work of Engle et al. (1990) and Greenwood-Nimmo et al. (2016), a growing number of studies show significant volatility connectedness among major currencies in different periods/economic conditions. For example, Greenwood-Nimmo et al. (2016) report evidence of currency connectedness/spillovers over the 1999–2014 period using an empirical network model (VAR). They show that spillover intensity increases during crisis periods. In a recent study, Wen and Wang (2020) examine the linkages of 65 major currencies (2000–2019) with LASSO-VAR approaches and find that currency volatility connectedness increases with financial crises. More importantly, Barunik et al. (2017) employ the volatility spillover index by Diebold and Yilmaz (2012) and the VAR approach to study the volatility connectedness of major currencies in the 2007–2015 period. They show supporting evidence for the asymmetric volatility connectedness among these currencies. Notably, different economic/policy events are associated with different spillover effects. Barunik et al. (2017) find that the sovereign debt crisis in Europe links with negative spillovers, while such events as the subprime crisis link with positive spillovers.

Crises offer unique and vital contexts to examine the economic shocks on various activities in the economy. Indeed, many studies have attempted to investigate the spillover contagion effects between different financial markets/sectors during crisis periods. For example, Nagayasu (2001) documents an upward pressure of sectoral stock indices on exchange rates and significant contagion effects from Thailand to the Philippines during the Asian crisis (1997–1998). Jin and An (2016) show evidence of the contagion effects between stock markets in the BRICS region and the US during the Global Financial Crisis (GFC, 2008–2009). Similarly, Laborda and Olmo (2021) show consistent evidence for the volatility connectedness/spillover between various economic sectors such as Energy, Banking and Insurance, and Technology during the GFC and the Covid-19 crisis.

Regarding the ongoing Covid-19 outbreak, prior research has documented the significant influence of the pandemic on various markets such as stock (Phan & Narayan 2020; Mazur et al. 2021), commodity (Hung & Vo 2021; Salisu et al. 2021), bond (Nozawa & Qiu 2021; Yi et al. 2021), and forex market (Feng et al. 2021; Narayan 2021). Informed to the literature, the Covid-19 outbreak, with its severe impacts and unique features, could bring about distinct changes in volatility connectedness and contagion effects among major currencies. Nevertheless, there is a lack of research on these issues. Thus, our study aims to address this gap and extends the third strand of literature by investigating the connectedness among major currencies during the Covid-19 outbreak using two new approaches: DECO-GARCH and Transfer Entropy.

3. Methodology

We first capture the equicorrelation among the selected exchange rate markets by utilizing the DECO-GARCH model developed by Engle and Kelly (2012). Second, we employ the Transfer Entropy approach to detect the causal association between the exchange rate returns.

3.1. DECO-GARCH model

This section illustrates the main characteristics of the DECO-GARCH model following (Hung 2020, 2021; Nguyen et al. 2021), which is recommended for carrying out high-dimension systems (Nguyen et al. 2021). The DECO model assumes that correlations among asset returns are equal. The common equicorrelation is, however, time-varying. The return on foreign exchange rate i at time t can be defined as follows:

$$r_i = \mu + \alpha r_{i-1} + \epsilon_i$$  \hspace{1cm} (1)

$$h^2_i = \omega + \alpha_\epsilon \epsilon^2_{i-1} + \beta h_{i-1} + \gamma \epsilon^2_{i-1}$$  \hspace{1cm} (2)

3
Where is the exchange rate return and $h_t^2$ presents the conditional variance. When $r_{t-1} < 0$, we have $d_{t-1} = 1$, $q$ shows the influences of previous squared errors in the present conditional volatility level, $\beta$ measures the impacts of lagged volatility on the present volatility, $\gamma$ measures the asymmetric impacts of negative and positive innovations.

Let’s denote $H_t$ as the conditional covariance matrix:

$$H_t = D_t^{1/2} R_t D_t^{1/2}$$

(3)

where the conditional correlation matrix is $R_t$, and the diagonal matrix of conditional variance is $D_t$.

The DECO specification is obtained based on the DCC model by Engle (2002), corresponding to the correlation matrix. $R_t^{DCC}$ can be written as:

$$R_t^{DCC} = (Q_t^{*})^{-1/2} Q_t (Q_t^{*})^{-1/2}$$

(4)

$$Q_t = (1 - \psi - \zeta) K + \psi \eta_{t-1} \eta_t^{*} + \zeta Q_{t-1}$$

(5)

where non-negative scalars $\psi$ and $\zeta$ must satisfy the condition $\psi + \zeta < 1$, $\eta_t$ presents the standardized residuals and unconditional covariance matrix of $\eta_t$ is $K$ (nxn). The square root of the diagonal components of the covariance matrix $Q_t$ form is:

$$Q_t^{*} = \text{diag}\left(\sqrt{Q_{ii}^{**}}\right).$$

An element of the $R_t^{DCC}$ is $q_{ij} = \frac{q_{ij}'}{\sqrt{q_{ii}'q_{jj}'}}$.

The conditional correlation matrix is defined in the equicorrelation form, as defined by Engle and Kelly (2012), as follows:

$$R_t^{DECO} = (1 - \rho_t) I_n + \rho_t J_n$$

(6)

where the conditional equicorrelation is $\rho_t$, $I_n$ is the $n$-dimensional identity matrix, and $J_n$ shows the unit matrix (nxn). The DECO model sets $\rho_t$ equal to the average DCC correlations, which is written as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)} \left( J_n R_t^{DCC} J_n - n \right) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij}'}{\sqrt{q_{ii}'q_{jj}'}}$$

(7)

The DECO model’s scalar version can be written as:

$$Q_t = (1 - \lambda - \pi) K + \lambda \eta_{t-1} \eta_t^{*} + \pi Q_{t-1}$$

(8)

It is worth noting that the model parameters are estimated using the quasi maximum likelihood (QML) method.  

3.2. Transfer Entropy approach

The information dependence between variables can be identified under the Transfer Entropy method developed by Shannon (1948). We adopt a similar approach to Huynh (2020) and Huynh et al. (2020).

Shannon (1948) defines Transfer Entropy as:

$$H_t = - \sum_j p(j) \log(p(j))$$

(8)

Where J represents the discrete random indicator with the probability distribution p(j), and j depicts the different results that this variable can produce. As a result, $H_t$ is the best possible value.

Renyi Entropy is proposed by Jizba et al. (2012) for a lead-lag association with the weighting parameter $q$. Kullback and Leibler (1951) define the generalized Markov process as follows:

$$p(i_{t+1}|j_t^{(i)}) = p(i_{t+1}|i_t^{(j)}, j_t^{(i)})$$

(9)

The escort distribution $\phi_q(j) = \frac{p(j)^{q-1}}{\sum_{j} p(j)^{q-1}}$ with $q > 0$ to normalize. Transfer Entropy can be written as:

$$TE_{X\rightarrow Y|i}(j) = \frac{1}{1-q} \log \left( \frac{\sum_{i,j} \phi_q(i^{(j)}, j^{(i)}) p(i_{t+1}|i_t^{(j)}, j_t^{(i)})}{\sum_{i,j} \phi_q(i^{(j)}, j^{(i)}) p(i_t^{(j)}, j_t^{(i)})} \right)$$

(10)

3.3. Data

The empirical analysis in this study is based on daily exchange rates against the US dollar of six internationally famous currencies: the Euro (EURO), the Canadian dollar (CAN), the British pound (GBP), the Australian dollar (AUD), the Swiss Franc (CHF), the Japanese yen (YEN). The sample period ranges from 1 January 2018 to 12 May 2021. We further divide the sample into two sub-

1 See Bollerslev and Wooldridge (1992) for further details.
Fig. 1. Daily return series for the six currencies from 2 January 2020 to 12 May 2021.
Fig. 1. (continued).
periods: (1) the pre-Covid period: from 1 January 2018 to 31 December 2020, and (2) the Covid-19 period: from 1 January 2020 to 12 May 2021. Many scholars consider January 2020 the start of the global Covid-19 crisis (Hung & Vo 2021; Kocaarslan & Soytas 2021). We use the Thomson Reuters Eikon database to collect the data. Each market has 356 daily observations over the sample period. The daily returns for each exchange rate market are calculated as logarithmic differences in daily market indexes. In Fig. 1, we graph the time return series plots of the six exchange rate indices. As shown in Fig. 1, we can observe that all the exchange rate markets experience long-swing fluctuations during the Covid-19 period.

Table 1 shows the descriptive statistics for the examined return series. As illustrated in Table 1, all mean values of the exchange rate returns are negative. More importantly, they exhibit high volatility as measured by the standard deviation of daily returns, implying that the Covid-19 outbreak has significantly influenced the selected exchange rate markets. There is also a significant difference between the maximum and minimum values, suggesting a remarkable effect of the Covid-19 pandemic. In addition, all the daily returns experience significant asymmetry, as shown by the skewness and kurtosis coefficients, indicating their leptokurtic distributions. The Jarque-Bera test statistics show that exchange rates are not normally distributed. Following the ADF test, we can reject the null hypothesis of the presence of a unit root for all the series (1 % significance level). As a result, we implement our analysis using the return series.

Fig. 2 depicts a graphical representation of the data’s overall distribution and the pair-wise correlation between returns. As shown in Fig. 2, the data distribution is not normal. The highest correlation (0.72) is observed between AUD and CAN returns. The lowest correlation, 0.14, is observed between YEN and CAN. Overall, Fig. 2 offers further insights into the examined exchange rate returns’ data distribution and correlation structure. Results also suggest a strong relationship between the variables.

4. Results

4.1. Dynamic volatility and equicorrelation of major exchange rates

Table 2 presents the time-varying correlations between the exchange rate markets under examination using the multivariate GARCH model with the DECO specification. The lag order of the GARCH model is chosen based on the Akaike information criteria (AIC). The table also shows the estimation findings of the mean, conditional variance, and conditional equicorrelation coefficients. The DECO-GARCH model is critical for understanding the interdependence between the variables’ volatilities.

The univariate GARCH coefficients are reported in Table 2. Specifically, all series ARCH and GARCH terms are statistically significant at the 1 % significance level. In addition, the sum of these coefficients is close to unity, suggesting stability. This also implies the persistence of shocks or the existence of volatility and unveils that conditional volatility is mean-reverting.

The main findings of the DECO model are shown in Tables 2 and 3, representing the pre and during the Covid-19 pandemic, respectively. The time-varying equicorrelation is significantly positive (0.344) during the pandemic. At the same time, this figure in the pre-Covid-19 period is lower, just around 0.044, indicating that the selected exchange rate markets are highly contagious during the Covid-19 period.

The estimates of diagnostic tests on the standard and squared standardized residuals are shown in Tables 2 and 3. The Ljung-Box test statistics for standard residuals and squared standardized residuals suggest not to reject the null hypothesis that there is no serial correlation in all cases. Besides, we also utilize multivariate portmanteau tests to ensure that the DECO model is valid. The test statistics of Hosking (1980) and McLeod and Li (1983) illustrate that the null hypothesis of no serial correlation in the conditional variances obtained by the DECO-GARCH model cannot be rejected. Therefore, we conclude that statistical misspecification of the DECO model is not supported. In other words, the statistical significance of the results and diagnostic tests support our decision to employ the DECO-GARCH model.

Further, we turn to an in-depth analysis of the co-movement across the exchange rate market returns. Figs. 3 and 4 describe the

Table 1
Descriptive statistics of sample return data during the COVID-19 period.

|          | EURO   | GBP    | AUD    | CHF    | YEN    | CAN    |
|----------|--------|--------|--------|--------|--------|--------|
| Mean     | -0.022572 | -0.019129 | -0.032399 | -0.020330 | -0.000493 | -0.019551 |
| Maximum  | 1.753970  | 2.720391  | 3.644672  | 2.120943  | 2.021916  | 2.392217  |
| Minimum  | -1.752801  | -3.129735  | -3.313965  | -1.980474  | -2.693895  | -2.033013  |
| Std. Dev | 0.445930  | 0.648187  | 0.752196  | 0.457317  | 0.467066  | 0.474020  |
| Skewness | 0.021103  | -0.019819  | 0.392439  | 0.211574  | -0.464079  | 0.473804  |
| Kurtosis | 4.559243  | 5.985588  | 7.083158  | 5.953178  | 8.506039  | 6.277862  |
| Jarque-Bera | 131.8723  | 255.7214  | 131.6505  | 461.1736  | 172.2096  | 6.277862  |
| ADF      | -16.3988  | -17.94793  | -18.0766  | -17.72518  | -16.58730  | -18.06029  |
| ARCH-LM  | 16.58730  | 18.0766  | 18.0766  | 19.920318  | 34.01208  | 9.785233  |

Notes: ADF is the computed statistics of the Augmented Dickey and Fuller unit root test. ARCH-LM checks for the presence of ARCH effects. ***, *** significant at 5% and 1%, respectively.
Fig. 2. The distribution and the pair-wise correlations of the exchange rate returns.

Table 2
Results of the DECO-GARCH model in the pre-COVID 19 period.

|                  | EURO | GBP | AUD | CHF | YEN | CAN |
|------------------|------|-----|-----|-----|-----|-----|
| Univariate GARCH model |      |     |     |     |     |     |
| \( \mu \)         | 0.010010 (0.015050) | -0.006849 | 0.006849 (0.022715) | 0.027788 (0.020324) | -0.002175 (0.015707) | 0.000548 (0.0016300) | -0.004825 (0.014240) |
| \( \nu \)         | 0.001071 (0.000559) | 0.039824 (0.037048) | 0.143975 (0.092988) | 0.006419 (0.004545) | 0.000548 (0.006915) | 0.004825 (0.000528) |
| ARCH              | 0.012801 (0.007835) | 0.045296 (0.024446) | 0.070710 (0.013506) | 0.067170 (0.029046) | 0.040388 (0.021693) | 0.016587 (0.007446) |
| GARCH             | 0.920604 (0.012293) | 0.803044 (0.156152) | 0.467450 (0.393647) | 0.882895 (0.055228) | 0.902424 (0.067348) | 0.982951 (0.009964) |
| Univariate diagnostic tests |      |     |     |     |     |     |
| Q(10)            | 7.4859 [0.278] | 7.5512 [0.673] | 8.2239 [0.607] | 9.6004 [0.476] | 8.6088 [0.570] | 10.957 [0.361] |
| Q^2(10)          | 2.5203 [0.284] | 15.270 [0.123] | 12.849 [0.232] | 5.8821 [0.825] | 12.654 [0.244] | 5.9723 [0.818] |
| ARCH-LM          | 0.231201 [0.6306] | 0.0273 [0.8686] | 0.90338 [0.3419] | 0.04981 [0.8234] | 0.30404 [0.581] | 0.1246 [0.724] |
| DECO model       |      |     |     |     |     |     |
| Average \( p_{ij} \) | 0.044203 (0.030114) | 0.05241026 (0.0368181) | 0.879571 (0.0806135) | 0.044203 (0.030114) | 0.05241026 (0.0368181) | 0.879571 (0.0806135) |
| Multivariate diagnostic tests |      |     |     |     |     |     |
| Hosking (10)     | 701.50 [0.443] | 717.58 [0.414] | 701.50 [0.443] | 717.58 [0.414] | 701.50 [0.443] | 717.58 [0.414] |

Notes: Q (10) and Q^2(10) are the Ljung-Box test statistics applied to the standard residuals and the squared standardized residuals, respectively. Standard errors are presented in the parentheses. Hosking (10) and McLeod-Li (10) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardized residuals (10 lags). P-values are shown in brackets. *, **, *** represent 10%, 5%, and 1% significance level, respectively.
Table 3
Results of the DECO-GARCH model during the COVID-19.

|   | EURO | GBP | AUD | CHF | YEN | CAN |
|---|------|-----|-----|-----|-----|-----|
| Univariate GARCH model | | | | | | |
| $\mu$ | -0.014913 | -0.037684 | -0.027969 | -0.015966 (0.059574) | 0.01018 (0.019227) | -0.005199 |
| (0.021201) | (0.03698) | (0.034951) | (0.027269) | (0.019227) | (0.021498) |
| $\nu$ | 0.008647*** | 0.028566*** | 0.024740*** | 0.036114*** | 0.020474*** (0.00649) | 0.008040*** |
| (0.004431) | (0.010905) | (0.007253) | (0.048770) | (0.003603) | |
| ARCH | 0.080775*** | 0.097075*** | 0.075596*** | 0.200357*** (0.048770) | 0.162657*** (0.038206) | 0.127232*** |
| (0.025394) | (0.025614) | (0.017117) | (0.007253) | (0.003603) | |
| GARCH | 0.875566*** | 0.827980*** | 0.878115*** | 0.632908*** | 0.731038*** (0.06344) | 0.843261*** |
| (0.041721) | (0.045855) | (0.024129) | (0.071163) | |
| Univariate diagnostic tests | | | | | | |
| $Q(10)$ | 16.029 [0.099] | 7.8366 [0.645] | 2.0660 [0.724] | 6.0645 [0.810] | 11.191 [0.343] | 8.3677 [0.593] |
| $Q^2(10)$ | 3.4326 [0.488] | 9.2212 [0.511] | 16.263 [0.092] | 5.7492 [0.836] | 7.1114 [0.715] | 14.403 [0.155] |
| ARCH-LM | 2.010960 [0.1562] | 0.451747 [0.5015] | 0.789 [0.3743] | 0.6191 [0.431] | 0.0101 [0.919] | 0.0188 [0.8909] |
| DECO model | | | | | | |
| Average $p_{ij}$ | 0.344034*** (0.0564) | 0.344034*** (0.0564) | 0.344034*** (0.0564) | 0.344034*** (0.0564) | 0.344034*** (0.0564) | 0.344034*** (0.0564) |
| $A_{DECO}$ | 0.0512** (0.0237) | 0.0512** (0.0237) | 0.0512** (0.0237) | 0.0512** (0.0237) | 0.0512** (0.0237) | 0.0512** (0.0237) |
| $B_{DECO}$ | 0.89802 (0.0566) | 0.89802 (0.0566) | 0.89802 (0.0566) | 0.89802 (0.0566) | 0.89802 (0.0566) | 0.89802 (0.0566) |
| Multivariate diagnostic tests | | | | | | |
| Hosking | 275.124 [0.315] | 275.124 [0.315] | 275.124 [0.315] | 275.124 [0.315] | 275.124 [0.315] | 275.124 [0.315] |
| (10) | | | | | | |
| McLeod-Li | 268.041 [0.390] | 268.041 [0.390] | 268.041 [0.390] | 268.041 [0.390] | 268.041 [0.390] | 268.041 [0.390] |
| (10) | | | | | | |

Notes: $Q(10)$ and $Q^2(10)$ are the Ljung-Box test statistics applied to the standard residuals and the squared standardized residuals, respectively. Standard errors are presented in the parentheses. Hosking (10) and McLeod-Li (10) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardized residuals (10 lags). P-values are shown in brackets. *, **, *** represent 10%, 5%, and 1% significance level, respectively.

Fig. 3. Dynamic equicorrelation of the selected foreign exchange rates in the pre COVID-19 outbreak.

Fig. 4. Dynamic equicorrelation of the selected foreign exchange rates during the COVID-19 outbreak.
Fig. 5. Dynamic conditional correlation between the selected exchange rate returns.
Fig. 5. (continued).
Fig. 5. (continued).
Fig. 5. (continued).
Fig. 5. (continued).
time-varying equicorrelation among the six exchange rate returns in both sub-samples. We observe time-varying equicorrelation during the test period, implying that investors occasionally adjust their portfolio structures for these assets. Specifically, the equicorrelation level rises steadily at the beginning of the Covid-19 outbreak, supporting the hypothesis of contagion effects (Kang et al. 2017; Hung & Vo 2021). This effect during stress periods may adversely affect international portfolio diversification (Aslam et al. 2020; Konstantakis et al. 2021). Furthermore, the equicorrelation coefficient remains positive in both periods. The equicorrelation goes beyond 0.1 during the Covid-19 pandemic, suggesting substantial volatility in exchange rate returns driven by the Covid-19 outbreak. The highest degree of equicorrelation reaches more than 0.45 between 2020 and 2021. Such findings align with several recent studies (e.g., Feng et al. 2021; Narayan 2021), which document a significant increase in exchange rate volatility during the COVID-19 outbreak.

The current study also estimates the dynamic conditional correlation models (DCC) between the variables under consideration for robustness check. As shown in Fig. 5, the DCC level between the exchange rate markets changes remarkably during the Covid-19 pandemic, indicating a contagion effect. As a result, the pair-wise dynamic conditional correlation affirms our results for the exchange rate markets based on the DECO estimations. We also look into the spillover effects among exchange rate time series using the connectedness indexes of Diebold and Yilmaz (2012). We observe a bidirectional relationship between the selected exchange rate returns (Table 4). As projected, the level of market influence during the Covid-19 pandemic is higher than before (pre-Covid period). Fig. 6 suggests that the Covid-19 outbreak triggers the spillover effects between significant exchange rate returns, providing further robust evidence for our findings.

4.2. Spillover effects in the exchange rate markets during the Covid-19 pandemic.

Table 5 shows the results of our estimation of transfer entropy values. It should be highlighted that correlations or coefficients do not support the directional or signal relationship. They should be interpreted as transfer entropy values (information flows) from Sender to Receiver (Huynh et al. 2020). Results reveal overall spillover effects across the exchange rate markets during the Covid-19 outbreak, as measured by the Transfer Entropy framework, in line with findings in other financial markets in the previous crises (e.g., Nagayasu 2001; Jin & An 2016; Laborda & Olmo 2021). As indicated in Table 5, EURO and YEN stand as the significant givers of shocks to other receiving currencies. A bi-causal relationship is found between EURO, CHF, and CAN. This scenario is actual for GBP-YEN, CHF-AUD, and YEN-CAN pairs. On the other hand, there is no relationship between CHF and GBP, AUD and CAN, GBP and CAN in terms of the information flow of returns, suggesting that the time-varying conditional equicorrelation is caused by systematic risks (Huynh, 2020). There is a mono-direction between the examined variables at the 10 % significance level for the rest of the cases. Moreover, while EURO and YEN appear to be the senders, AUD and CHF tend to be the receivers. EURO, GBP, and AUD are the leading currencies ranked by both from-degree and to-degree connectedness. For example, EURO (ranked 2nd), GBP (ranked 3rd), and AUD (ranked 5th) is the highest receivers and senders, respectively. These three currencies are among widely traded currencies with high trading volumes, explaining their substantial impacts. Overall, EURO, YEN, and CAN are dominant in the forex markets under consideration, and their connectedness may be attributed to the direction between the other pairs.

5. Discussion and conclusion

We find supporting evidence for high volatility and a significant positive equicorrelation among major exchange rates during the Covid-19 pandemic. Our paper documents contagion effects, significantly affecting investors’ and firms’ risk management strategies. Exchange rates are likely to exhibit high volatility in turmoil periods under unstable macroeconomic and financial environments (Konstantakis et al. 2021). The Covid-19 outbreak is claimed to cause the most severe crisis after World War II (OECD 2020c). As a result, central banks in many countries have lowered their interest rates and offered various stimulus packages (Bloomberg 2021; Konstantakis et al. 2021). Furthermore, Covid-19 has had severe impacts on the global trade chain (e.g., international trade could drop by 12 % to 32 % (WTO 2020)). FDI flows could also decrease by approximately 40 % in 2020 (OECD 2020b). Given the fast-evolving Covid situation in many countries, there is high uncertainty in economic policy. Our findings of high exchange rate volatility are thus consistent with Krol (2014), who documents a significant positive relationship between financial and economic policy uncertainty and exchange rate volatility in various countries. Similar findings are also reported in recent studies about the pandemic (e.g., Feng et al. 2021; Narayan 2021). During turmoil periods with negative emotions, fears, and sadness prevalent in international news headlines, investors’ return expectations and risk characteristics are found to change significantly, leading to significant shifts in their risk-taking and trading behaviors (Hoffmann et al. 2013; Ortmann et al. 2020). Specifically, investors are found to use less leverage but still trade actively and intensively (Hoffmann et al. 2013; Ortmann et al. 2020). This could also explain the high volatility documented in our paper.

While previous studies have documented significant contagion effects in various financial markets across countries during/after crisis periods (van Horen et al. 2006; Baur 2012; Ranta 2013; Jin & An 2016; Abuzayed et al. 2021; Banerjee 2021; Wang et al. 2021), little research has investigated the forex market contagion during the Covid-19 outbreak, given its severe impacts on many economies. For example, van Horen et al. (2006) find supporting evidence for foreign exchange market contagion during the Asian financial crisis (1997–1998). Wang et al. (2021) examine the economic contagion effects among forex markets during the global financial crisis (2008–2009). Abuzayed et al. (2021) study the contagion effects during the Covid-19 crisis but focus on the global and individual stock markets. We extend this line of literature by examining the contagion effects amidst the Covid-19 pandemic and document consistent findings. Understanding the contagion effects among widely traded currencies is crucial for firms and investors in their risk hedging (Wang et al. 2021) and international diversification strategies (Forbes & Rigobon 2001).
Table 4
Spillover index.

|          | AUD  | CAN  | CHF  | EURO | GBP  | YEN  | From others |
|----------|------|------|------|------|------|------|-------------|
| Pre-COVID|      |      |      |      |      |      |             |
| AUD      | 96.0 | 1.0  | 0.5  | 1.1  | 0.8  | 0.7  | 4.0         |
| CAN      | 37.5 | 60.0 | 0.7  | 0.8  | 0.3  | 0.7  | 40.0        |
| CHF      | 13.9 | 0.6  | 83.7 | 0.3  | 0.5  | 0.9  | 16.3        |
| EURO     | 35.6 | 1.6  | 27.2 | 32.8 | 1.7  | 1.1  | 67.2        |
| GBP      | 18.7 | 1.9  | 8.6  | 9.1  | 61.0 | 0.7  | 39.0        |
| YEN      | 2.6  | 0.6  | 32.1 | 0.8  | 0.3  | 63.6 | 36.4        |
| Contribution to others | 108.3 | 5.7 | 69.2 | 12.0 | 3.6 | 4.1 | 202.9 |
| Contribution including own | 204.3 | 65.7 | 152.9 | 44.8 | 64.6 | 67.7 | Spillover index = 33.8 % |

|          | AUD  | CAN  | CHF  | EURO | GBP  | YEN  | From others |
|----------|------|------|------|------|------|------|-------------|
| During COVID |      |      |      |      |      |      |             |
| AUD      | 92.6 | 0.7  | 3.9  | 1.4  | 0.3  | 1.1  | 7.4         |
| CAN      | 49.7 | 44.4 | 2.5  | 0.9  | 1.2  | 1.3  | 55.6        |
| CHF      | 21.2 | 2.8  | 74.5 | 0.6  | 0.2  | 0.7  | 25.5        |
| EURO     | 33.6 | 2.5  | 39.2 | 23.5 | 0.4  | 0.9  | 76.5        |
| GBP      | 47.5 | 2.3  | 7.4  | 1.5  | 40.1 | 1.2  | 59.9        |
| YEN      | 10.1 | 8.0  | 26.0 | 3.4  | 4.2  | 48.3 | 51.7        |
| Contribution to others | 162.0 | 16.3 | 78.9 | 7.8  | 6.3  | 5.1  | 276.5 |
| Contribution including own | 254.6 | 60.8 | 153.5 | 31.3 | 46.4 | 53.5 | Spillover index = 46.1 % |

Notes: These results are computed based on the framework of spillover index of Diebold and Yilmaz (2012).

Table 5
Transfer entropy matrix.

| SENDER | EURO   | GBP   | AUD   | CHF   | YEN   | CAN   |
|--------|--------|-------|-------|-------|-------|-------|
| RECEIVER | 0.0122 (0.006) | 0.0216 (0.0068) | 0.0357* (0.0071) | 0.0144 (0.0066) | 0.0377†* (0.0071) |
| EURO   | 0.0264* (0.0079) | 0.0239 (0.0081) | 0.0213 (0.0085) | 0.0213 (0.0085) | 0.0487†* (0.0082) | 0.0229 (0.0076) |
| GBP    | 0.0401 †* (0.0079) | 0.0274 (0.0080) | 0.0356 †* (0.0074) | 0.0356 †* (0.0074) | 0.0287* (0.0086) | 0.0112 (0.0077) |
| AUD    | 0.0984 †* (0.0071) | 0.0225 (0.0034) | 0.0315 †* (0.0084) | 0.0315 †* (0.0084) | 0.0602* (0.0083) | 0.0401* (0.0079) |
| CHF    | 0.0454* (0.0078) | 0.0520 †* (0.0076) | 0.0328* (0.0082) | 0.0150 (0.0077) | 0.0309* (0.0075) |
| YEN    | 0.0318* (0.0069) | 0.0106 (0.0066) | 0.0173 (0.0065) | 0.0406 †* (0.0069) | 0.0318 †* (0.0067) |

Notes: The main value outputs are the Shannon transfer entropy (Dimpfl and Peter, 2013) with n = 300 and we dropped k = 50, considered as the burning values. The number of shuffles is selected randomly as 100 observations. Standard errors are presented in the parentheses. *, †, ‡ significant at 10 %, 5 % and 1 %, respectively.
According to Gil-Alana and Carcel (2020), exchange rates (against the US exchange rate) may represent characteristics shared by long memory processes. Thus, finding their causal associations might be accomplished through various advantages. This study examines the spillover effects across six exchange rates (i.e., AUD, CAD, CHF, EUR, JPY, GBP) with respect to USD) using both the multivariate DECO-GARCH and the Transfer Entropy models. We contribute to the exchange rate literature by taking novel techniques to investigate the co-movements of exchange rate returns. We study the spillover effects by classifying three groups of exchange rate markets (uni-direction, bi-direction, and no effect) based on sending-receiving risk to a specific exchange rate market under the Transfer Entropy approach. EURO and YEN stand as the large givers of shocks to other receiving currencies. Specifically, a bi-causal relationship between EURO, CHF, and CAN is found. However, there is no relationship between CHF and GBP, AUD and CAN, GBP and CAN in terms of the information flow of return.

We offer important implications for portfolio managers/investors, firms, and policymakers, particularly during stressful periods by uncovering the significant spillover effects among the currencies. First, our findings can provide valuable information for portfolio managers/investors to improve their trading decisions and risk management strategies. Understanding the spillover risks (and the direction of the spillover) is helpful for investors/traders to develop appropriate risk diversification strategies for their currency portfolios. Second, firms can build on our findings to refine their currency risk hedging strategy during turbulent periods. The significant spillover effects among widely traded currencies during the Covid-19 outbreak can be partly explained by its disruptive impact on international trade, global supply chains, and capital flows. Due to the lockdown across many countries, both firms and consumers tend to cut down their investment and consumption, leading to a significant decline in aggregate demand and production (Padhan & Prabhseel 2021). Thus, during such crisis periods, knowledge about the spillover effects among the major currencies is helpful for firms to develop hedging strategies to mitigate foreign exchange risks. Third, understanding the interdependence among financial markets, especially in turmoil periods, is relevant for policymakers to measure systemic financial risk (Abuzayed et al. 2021). Consistent with Bouri et al. (2020), our findings on the co-movements and spillover effects among major currencies during the Covid-19 period are important for regulators to assess better the systemic risk and potential adverse effects from excessive spillovers in the foreign exchange markets. Following that, policymakers can have appropriate policies and surveillance mechanisms to effectively manage risks and potential negative impacts from extreme currency risk spillovers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aboura, S., Chevallier, J., 2014. Cross-market spillovers with ‘volatility surprise’. Rev. Financial Econ. 23 (4), 194–207.
Abuzayed, B., Bouri, E., Al-Fayoumi, N., Jalkh, N., 2021. Systemic risk spillover across global and country stock markets during the COVID-19 pandemic. Econ. Anal. Policy 71, 180–197.
Al-Abri, A., Baghestani, H., 2015. Foreign investment and real exchange rate volatility in emerging Asian countries. J. Asian Econ. 37, 34–47.
Aslam, F., Aziz, S., Nguyen, D.K., Mughal, K.S., Khan, M., 2020. On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. Technol. Forecast. Soc. Chang. 161, 120261.
Banerjee, A.K., 2021. Futures market and the contagion effect of COVID-19 syndrome. Finance Res. Lett. 43, 102018.
Barunik, J., Kocenda, E., Vacha, L., 2017. Asymmetric volatility connectedness on the forex market. J. Int. Money Finance 77, 39–56.
Barunik, J., Kreihik, T., 2018. Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk*. J. Financial Econometrics 16, 271–296.
Baur, D.G., 2012. Financial contagion and the real economy. J. Bank. Finance 36 (10), 2680–2692.
BIS, 2020. US dollar still dominates international funding markets. Bloomberg, 2021. Ultra-Low Interest Rates Are Here to Stay: 2021 Central Bank Guide. URL https://www.bloomberg.com/news/articles/2021-01-05/ultra-low-interest-rates-here-to-stay-2021-central-bank-guide.
Bouri, E., Lacoy, B., Saeed, T., Vo, X.V., 2020. Extreme spillovers across Asian-Pacific currencies: a quantile-based analysis. Int. Rev. Financial Anal. 72, 101605.
Cai, X.J., Tian, S., Hamori, S., 2016. Dynamic correlation and equicorrelation analysis of global financial turmoil: evidence from emerging East Asian stock markets. Appl. Econ. 48 (40), 3789–3803.
Coudert, V., Cougharde, C., Mignon, V., 2011. Exchange rate volatility across financial crises. J. Bank. Finance 35 (11), 3010–3018.
Dang, T.T., Zhang, C., Nguyen, T.H., Nguyen, N.T., 2020. Assessing the influence of exchange rate on agricultural commodity export price: evidence from Vietnamese coffee. Journal of Economics and Development 22, 297–309.
Demiralay, S., Golitsis, P., 2021. On the dynamic equicorrelations in cryptocurrency market. Quart. Rev. Econ. Finance 80, 524–533.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Dimpf, T., Peter, F., 2013. Using transfer entropy to measure information flows between financial markets. Stud. Nonlinear Dyn. Econometrics 17, 85–102.
Engle, R., Itu, T., Lin, W.-L., 1990. Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market. Econometrica 58, 525–542.
Engle, R., Kelly, B., 2012. Dynamic Equicorrelation. J. Bus. Econ. Statistics 30 (2), 212–228.
Feng, G.-F., Yang, H.-C., Gong, Q., Chang, C.-P., 2021. What is the exchange rate volatility response to COIVD-19 and government interventions? Econ. Anal. Policy 69, 705–719.
Forbes, K., Rigobon, R., 2001. Measuring Contagion: Conceptual and Empirical Issues. In: Claessens, S., Forbes, K.J. (Eds.), International Financial Contagion. Springer US, Boston, MA, pp. 43–66.
Gil-Alana, L.A., Carcel, H., 2020. A fractional cointegration var analysis of exchange rate dynamics. North Am. J. Eco. Finance 51, 100848.
Greenwood-Nimmo, M., Nguyen, V.H., Rafferty, B., 2016. Risk and return spillovers among the G10 currencies. J. Financial Markets 31, 43.
Hosking, J.R.M., 1980. The multivariate portmanteau statistic. J. Am. Stat. Assoc. 75 (371), 602.
Hung, N.T., Vo, X.V., 2021. Directional spillover effects and time-frequency nexus between oil, gold and stock markets: Evidence from pre and during COVID-19 outbreak. Int. Rev. Financial Anal. 76, 101730.

