International Journal of Applied Economics, Finance and Accounting
ISSN 2577-767X
Vol. 17, No. 1, pp. 156-167
2023
DOI: 10.33094/ijaefa.v17i1.1092

COVID-19 pandemic, Russian-Ukrainian war and REER volatility: Evidence from panel of countries

Ayyoub Ben El Rhadbane[1*]
Abdeslam El Moudden[2]

[1,2]*Ibnou Tofail University, National School of Business and Management, Kenitra, Morocco.*
[1]*Email:* benelrhadbaneayyoub@gmail.com
[2]*Email:* elmoud@yahoo.com

Keywords:
ARCH-GARCH
ARDL panel
COVID-19
REER
Russian-Ukrainian war.

JEL Classification:
E42; F50; G01.

Received: *12 April 2023*
Revised: *3 July 2023*
Accepted: *24 July 2023*
Published: *10 August 2023*
(Corresponding Author)*

Abstract

This article aims to empirically study the effect of the COVID-19 pandemic and the Russian-Ukrainian war on the volatility of the real effective exchange rate (REER) using panel data from 23 advanced, emerging, and developing economies. The study covers the period from January 2020 to October 2022. The ARCH/GARCH model is used to estimate the monthly REER volatility for each monetary zone. The impact of the COVID-19 pandemic is measured by the monthly Covid- 19 deaths, while the Russian-Ukrainian war is measured using two factors: monthly oil prices in USD and the monthly food price index. Consequently, two models are developed: the first one measure the impact of the COVID-19 deaths and the oil prices, while the second assesses the impact of the COVID-19 deaths and the food price index on the REER volatility. In both models, the long-term results suggest that the COVID-19 pandemic and the Russian-Ukrainian war have a positive and significant effect on REER volatility at a 1% significance level. Moreover, the Granger test suggests that the independent variables cause REER volatility at a 1% significance level. Finally, the study concludes that the Russian-Ukrainian war significantly intensifies REER volatility more than the COVID-19 pandemic.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Data Availability Statement: The corresponding author may provide study data upon reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

1. Introduction

During the period from 2020 to 2022, the world economy experienced substantial fluctuations and severe upheavals primarily attributed to the COVID-19 pandemic and the Russian-Ukrainian war. The extensive funds mobilized and injected, along with measures such as lockdowns, implemented by authorities in each country, resulted in an unprecedented economic mega-crisis in its extent, progression, and severity. This exogenous, unpredictable, and global crisis undermined the performance of the global economy, leading to significant consequences across all levels.

The Global Domestic Product (GDP) recorded a significant drop of almost 3.2% in 2020. However, it showed signs of recovery with growth rates of 6% and 3.2% in 2021 and 2022, respectively (*source: International Monetary Fund*). Furthermore, the economic growth witnessed in 2020 was even worse than that observed during the 2009 financial crisis (El Rhadbane & El Moudden, 2022). In response to this economic recession caused by both supply shocks such as drops in production and disruption in the global supply chain, as well as demand shocks including declines in domestic and external demand, governments worldwide launched economic support programs and implemented recovery plans. The objective was to facilitate effective economic recovery and ensure stronger economic resilience in the future.

For example, in March 2020, the United States of America (USA) launched its first support program called *Coronavirus Aid, Relief, and Economic Security Act (CARES Act)*. This program had a budget of 2.2 trillion dollars, equivalent to 18% of the US GDP, aimed at providing support to households and businesses. Subsequently, a second support program with a funding amount of 900 billion dollars was approved in December 2020. In March 2021, a third support program worth 1900 billion dollars was injected into the American economy in order to stimulate more economic growth.

Turning to the European Union, an economic support program called *NextGenerationEU* was adopted in June 2020. This program carried a total budget of 806.9 billion euros and had a fundamental objective to emerge stronger from the COVID-19 pandemic crisis.

However, the outbreak of the Russian-Ukrainian war on February 24, 2022, raised concerns about the effectiveness of these massive stimulus programs in terms of allocated budgets. This conflict resulted in a significant disruption of global trade flows, commodity markets, and capital markets. It is worth noting that both Russia and Ukraine are regarded as major producers of energy and essential food items on a global scale. In fact, over the past five years, Russia and Ukraine have accounted for an average of 10% and 3% respectively of world wheat production (*Source: OECD*).

Additionally, it is important to note that Russia is the world's largest natural gas exporter, accounting for 20% of the total in 2019. Furthermore, it is the second largest oil exporter, representing 11% of global oil exports, and the third largest coal exporter, accounting for 15% (*Source: Organisation for Economic Co-operation and Development (OECD)*). Therefore, numerous countries, including the USA, Brazil, Europe, Morocco, Egypt, South Africa, etc. have experienced significant inflationary pressures. "*The global economy remains weakened by the war due to major trade disruptions and volatile fuel and food prices, all of which are leading to high inflation and tighter global financing conditions* "[1].

In addition, the prevailing uncertainty and panic generated by this critical situation, encompassing both the COVID-19 pandemic and the Russian-Ukrainian war, have had a profound impact on both micro and macroeconomic balances. These events have shaken commodity and capital markets, contributing to an overall destabilization. Consequently, the exchange rate has been particularly susceptible to the strains of this ongoing economic asphyxiation.

In July 2022, the value of the US dollar, recognized as a safe haven, surpassed that of the euro for the first time in two decades. It is noteworthy that during this period, the inflation rate in the United States was higher compared to the European Union, standing at 9% versus 8%, respectively. Consequently, the exchange rate has also suffered the consequences of these two successive crises.

This article aimed to examine and analyze the effect of the COVID-19 pandemic and the Russian-Ukrainian war on the REER volatility. The second section presents the literature review on the relationship between "COVID-19 & exchange rate" and "Russian-Ukrainian war & exchange rate". The third section covers the data and methodology employed in the study. The fourth and fifth sections delve into the presentation of results and the conclusion, respectively.

2. Literature Review

2.1. COVID-19 Pandemic and Exchange Rate

The adverse micro and macro-economic effects resulting from the COVID-19 pandemic and the Russian-Ukrainian war have spurred numerous scientific research endeavours aimed at analysing the behavior of various economic and financial indicators within this critical economic context. Notably, several studies have the relationship between the COVID-19 pandemic and the exchange rate.

For instance, Kohrt, Horky, and Fidrmuc (2022) conduct an analysis on the effect of the COVID-19 pandemic on the real exchange rates of 16 emerging countries, including Brazil, South Africa, Chile, Mexico, Colombia, Turkey, Poland, Hungary, Czech, India, China, Thailand, Indonesia, Malaysia, Philippines, and South Korea. The study covered the period from January 2013 to July 2020, utilizing the behavioral equilibrium exchange rate approach augmented with pandemic variables. The results confirmed that the behavioral factors linked with the first wave of the COVID-19 pandemic played a significant role in explaining the behaviour of realexchange rates in the examined emerging countries. Thus, the real exchange rates were found to be influenced more by COVID-19 deaths rather than COVID-19 infections.

Subsequently, Aquilante, Di Pace, and Masolo (2022) conducted their study by estimating daily linear regressions and autoregressive vector panel models to examine the impact of COVID-19 news on the exchange rates of 57 countries. The analysis covered the period from January 2020 toJuly 2020. The results suggest that the dissemination of negative pandemic-related news leads to an immediate and statistically significant depreciation of the national currency against a basket of trade-weighted currencies.

[1]Press release of October 04, 2022 from the World Bank.

In a similar vein, Beirne, Renzhi, Sugandi, and Volz (2021) examined a fixed effect model for panel data and the structural autoregressive vector approach to investigate the effect of the COVID-19 pandemic on exchange rates across 38 emerging and advanced economies. These economies included eighteen European economies, eleven Asian economies, four Latino-American economies, and two African economies, as well as Australia, New Zealand, and the United States. The study spanned from January 4, 2010 to August 31, 2020. The findings revealed discovered that emerging markets, particularly in Asia and European, were more strongly impacted by the COVID-19 pandemic compared to advanced economies.

Furthermore, Sethi, Dash, Swain, and Das (2021) conducted a study examining the effect of the COVID-19 pandemic on exchange rate behavior in 37 developed and developing countries. The analysis covered the period from January 4, 2020 to April 30, 2021. The results obtained from fixed-effect regression models indicated that the exchange rates exhibited a positive response to the COVID-19 pandemic, particularly in relation to confirmed cases and daily deaths. Consequently, the value of other currencies in comparison to the US dollar experienced depreciation. However, the study found that the effect of the World Pandemic Uncertainty Index (WPUI) seems to be insignificant. Moreover, the study highlighted the presentence of an asymmetric effect of COVID-19 on the exchange rate across different time periods.

Subsequently, Zhou, Yu, Li, and Qin (2021) conducted an analysis to examine the relationship between rare disasters, including the COVID-19 pandemic, macroeconomic policy, and exchange rates. The study focused on 27 advanced and emerging economies. The findings confirm a strong correlation between the COVID-19 pandemic and time-varying risk premiums in the foreign exchange market. Specifically, the spread of the COVID-19 pandemic resulted in s significant depreciation of domestic exchange rates in emerging markets, while advanced countries did not experience the same effect. The authors employed a fixed effects regression model for panel data to carry out this econometric study.

Following that, Klinlampu , Rakpho , Tarapituxwong , and Yamaka (2022) conducted a study exploring the nonlinear effect of the COVID-19 pandemic on the exchange rates of the British pound, European euro, and Chinese yuan against the US dollar. They employed a Markov regression model that switches between depreciation and appreciation regimes to analyse the currency market. The study confirmed that COVID-19 infections and deaths have the potential to cause currency depreciation. Additionally, they found that Google Trends, which serves as an indicator of panic and fear among investors during the pandemic, is likely to have a negative effect on the foreign exchange markets.

Thus, Narayan (2022) conducted an analysis on the role of exchange rate shocks in explaining the dynamics of other exchange rates, specifically the Euro, the Yen, the Canadian Dollar (CAD), and the British Pound Sterling (GBP). The study covered the period from July 2019 to September 2020, focusing on a 17 hour interval per day, from 02:00 to 17:00. By using a dynamic autoregressive vector model fitted to hourly data, the study confirmed an increase in the significance of exchange rate shocks in explaining the movements of other exchange rates during the study period, as compared to the pre-COVID-19 period. The analysis showed that exchange rate shocks of the respective currencies explained between 55% and 75% of their own exchange rate fluctuations.

Similarly, Shahrier (2022) conducted a study on the pure and fundamental-based contagion effects of the exchange rates among the Association of Southeast Asian Nations (ASEAN-5) during the COVID-19 period. The study covered the period from June 2019 to December 2020. Using the wavelet power spectrum approach, the analysis showed that Indonesia, Malaysia, and Singapore experienced a high and prolonged degree of exchange rate volatility. Thailand exhibited light volatility in the short term and high volatility in the longterm, while the Philippines showed only light volatility in the short term without an increase in the long term. Furthermore, employing the wavelet coherence approach, the study demonstrated that the Indonesian rupiah reacted first to the COVID-19 shock, leading to fundamental-based contagion effects in Malaysia and Thailand, and pure temporary sentimental-based contagion effects in the Philippines and Singapore. Notably, the Philippine peso appeared to isolate itself from long-term shocks.

Thus, Jamal and Bhat (2022) conducted a study exploring the relationship between the COVID-19 crisis and the exchange rate movements in six main COVID-19 hotspots, namely Brazil, China, India, Italy, Turkey, and the United Kingdom. The study covered the period from July 01, 2019 to September 3, 2020. Using the ARDL model, the results revealed a long-term causality from COVID-19 deaths to the exchange rate. Specifically, the coefficient of COVID-19 deaths was found to be positively significant and played a role in explaining the long-term exchange rate behavior. These findings were attributed to the impact of the COVID-19 pandemic on financial market expectations regarding the future value of the exchange rates in the main hot spots. Consequently, countries experiencing a significant daily increase in COVID-19 deaths have generally witnessed a weakening of their national currencies.

Feng, Yang, Gong, and Chang (2021) conducted an analysis on the effect of the COVID-19 pandemic on exchange rate volatility for a panel of 20 advanced and emerging countries. The study covered the period from January 13, 2020 to July 21, 2020. Utilizing the generalized method of moments, the study confirmed that an increase in confirmed cases of COVID-19 led to a corresponding intensification of exchange rate volatility.

2.2. Russo-Ukrainian War and Exchange Rates

As for the effect of the Russian-Ukrainian on the exchange rate, Sokhanvar and Bouri (2023) studied its impact on the Canadian dollar, the Euro, and the Japanese yen. They measured this impact through commodity price shocks resulting from the war in Ukraine. Using a dynamic ARDL model, they confirmed a positive effect of commodity price shocks on the value of the Canadian dollar against the Euro and the Yen. Thus, the analysis based on the quantile autoregressive distributed lag model suggests a long-term association between rising commodity prices and the appreciation of the Canadian dollar against the Euro and the Yen, during the period from February 01 and April 30, 2020.

Additionally, Tiwari, Singh, Kargeti, and Chand (2022) conducted an analysis on the effect of the war between Russia and Ukraine on theexchange rate between the Indian rupee and the US dollar. The result of the t-test indicated a negative effect of the war on the Indian rupee exchange rate. The country's heavy dependence on imports of energy, food and defense equipment had limited its ability to safeguard its currency and protect the livelihoods of its citizens during a 120-day period encompassing the time before and after the outbreak of the war.

This study aims to examine the effects of both the COVID-19 pandemic and the Russian-Ukrainian war on the REER volatility in 23 advanced, emerging, and developing economies. The analysis will cover the period from January, 2020 to October, 2022.

3. Databases and Methodology

3.1. Databases

To examine the effects of the COVID-19 pandemic and the Russian-Ukrainian war on the REER volatility, we use panel data from 23 economies. These economies include Australia, Brazil, Canada, China, India, Japan, Russia, United Kingdom, Turkey, USA, Euro Zone, Algeria, Azerbaijan, Bulgaria, Denmark, Egypt, Indonesia, Jordan, Mexico, Morocco, Nigeria, South Africa, and Tunisia. This empirical study incorporates data from sources such as Bruegel REER, the WorldHealth Organization, the United Nations, and the World Bank. Table 1 presents the variables that will be used in our two models along with their respective data sources.

Table 1. Database overview.

Variables	Sources
REER volatility "LvolREER"	Bruegel REER database, 12 September 2022
Number of deaths "Ldies"	World health organization (WHO)
Price of oil barrel "Lpo"	World bank
Food price index "Lfpi"	Food and agriculture organization of the united nations

3.1.1. Dependent Variable

The REER is an important economic indicator widely used in both theoretical and applied economic research. It measures the changes in the value of a country's currency, adjusted for price levels, against a basket of its trading partners. In other words, it is calculated by dividing the nominal effective exchange rate by a price deflator or a cost index. It is worth noting that the REER volatility is typically expressed in logarithmic form.

3.1.2. Independent Variables

In order to study the effect of the COVID-19 pandemic on the REER volatility, the pandemic itself is measured by the number of monthly COVID-19 deaths recorded in each country from January 2020 to October 2022. It is important to note that the values of this variable are expressed in logarithmic form.

In the first model, the Russian-Ukrainian war is measured by the monthly evolution of oil prices in USD, as published by the World Bank, during the period from January 2020 to October 2022. Notably, there was a significant in oil barrel prices following the outbreak of the war between the two neighboring countries. Prices rose from $72.78 in December 2021 to $93.45 in February 2022, $112.40 in March 2022 and $116.8 in June 2022. It should be noted that the values taken by this variable are expressed in logarithmic form.

Figure 1 illustrates the monthly evolution of oil barrel prices in USD from January 2018 to December 2022.

Figure 1. Monthly evolution of the oil barrel prices in USD over the period January 2018 - December 2022.
Source: OECD.

In the second model, the Russian-Ukrainian war is measured by the evolution of the food price index published by the Food and Agriculture Organization of the United Nations during the period from January 2020 to October2022. This index serves as a measure of the monthly change in international prices of five commodities: meat, dairy, cereals, oils, and sugar. Notably, the food price index also recorded a significant increase following the outbreak date of the war. It rose from 133.69 in December 2021 to 141,23 in February 2022, 159.71 in March 2022, and 158.05 in May2022. It is important to note that the values of this variable are expressed in logarithmic form.

Figure 2 illustrates the monthly evolution of the food price index from January 2018 to December 2022.

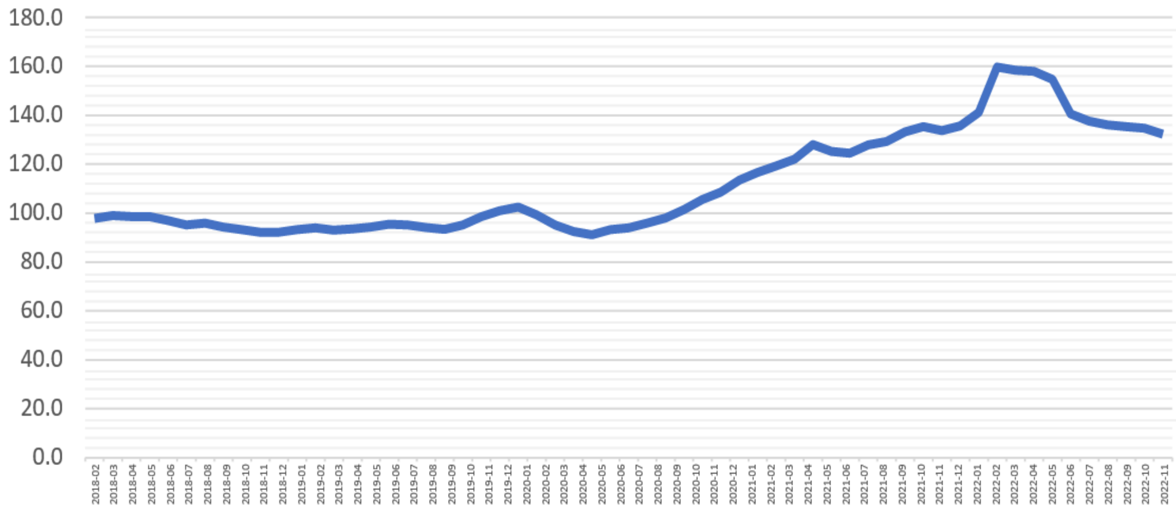

Figure 2. Monthly evolution of the food price index over the period January 2018 - December 2022.
Source: Food and Agriculture Organization of the United Nations.

3.2. Methodology

To conduct the present study, we employ the Autoregressive Distributed Lags (ARCH) / Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Autoregressive Distributed Lags (ARDL) of the panel to verify the effect of the two exogenous variables on the calculated REER volatility. Therefore, we follow the steps outlined below:

- **Step one: ARCH/GARCH modeling**

In the first step, we apply a heteroscedasticity test to determine the presence of an ARCH effect in the REER series for each currency. The results, presented in Table 2 confirm the presence of the ARCH effect across all 23 economies. Thus, Table 2 provides a summary of the results obtained from the ARCH (1) and GARCH (1,1) models. The estimates show that the coefficients of the variance equation significantly differ from zero and satisfy the constraints ensuring the positivity of the variance.

Table 2. Heteroscedasticity test.

Individual	Heteroscedasticity test		ARCH model		GARCH model		Selected model
	Chi2	Lag	Coefficient	Lag	Coefficient	Lag	
Australia	34.395***	1	0.146***	1	0.650***	1	GARCH(1.1)
Brazil	46.206***	1	0.261***	1	0.171	1	ARCH (1)
Canada	0.171***	7	0.102***	1	0.863***	1	GARCH(1.1)
China	15.745**	7	1.749***	1	0.117*	1	GARCH(1.1)
India	13.645**	5	0.008***	1	1.009***	1	GARCH(1.1)
Japan	57.609***	1	0.477***	1	-0.036	1	ARCH (1)
Russia	72.437***	1	1.334**	1	0.159***	1	GARCH(1.1)
United Kingdom	13.122***	1	0.171***	1	0.709***	1	GARCH(1.1)
Turkish	29.987***	1	0.320***	1	0.342***	1	GARCH(1.1)
USA	3.526*	1	0.159***	1	0.627***	1	GARCH(1.1)
Eurozone	6.300***	2	0.113***	1	0.810***	1	GARCH(1.1)
Algeria	12.285*	7	0.345***	1	0.653***	1	GARCH(1.1)
Azerbaijan	13.954***	1	0.412***	1	0.660***	1	GARCH(1.1)
Bulgaria	4.605**	1	0.379***	1	0.620***	1	GARCH(1.1)
Denmark	17.002	1	0.223***	1	0.491***	1	GARCH(1.1)
Egypt	14.284*	1	1.578***	1	0.134***	1	GARCH(1.1)
Indonesia	60.252***	1	0.914***	1	0.251***	1	GARCH(1.1)
Jordan	6.744***	1	0.0963**	1	0.715***	1	GARCH(1.1)
Mexico	13.873***	1	0.325***	1	0.107***	1	ARCH (1)
Morocco	43.809***	1	0.826***	1	0.210***	1	GARCH(1.1)
Nigeria	16.475*	1	1.593***	1	1.593***	1	GARCH(1.1)
South Africa	13.284*	1	0.485***	1	-0.034	1	ARCH (1)
Tunisia	43.799***	1	0.551***	1	0.088	1	ARCH (1)

Note: ***, ** and * represent statistical significance at 1%, 5% and 10% respectively. Source: Stata estimatesSo the ARCH (1) and GARCH (1,1) models measure the monthly REER volatility for each economy.

- **Step two: Correlation matrix**

The results of the correlation matrix, presented in Table 3, show a strong correlation between the variables of oil prices and the food price index. However, the correlation between COVID-19 deaths-oil prices, as well as COVID-19 deaths and the food price index, remains low.

Table 3. Correlation matrix.

Variables	Ldies	Lpo	Lfpi
Ldies	1.000		
Lpo	0.042	1.000	
Lfpi	0.142	0.942	1.000

- **Step three: Multicollinearity test**

Based on the multicollinearity test/vif, the results in Table 4 confirm that the oil prices and the food price index pose a problem of moderate multicollinearity with a VIF value greater than 5.

Table 4. Multicollinearity statistics before adjustment-VIF.

Variables	VIF	1/VIF
Ldies	9.860	0.101
Lpo	9.670	0.103
Lfpi	1.110	0.904
Mean VIF	6.880	

To address this issue of multicollinearity, we first analyze the impact of COVID-19 deaths and oil prices on REER volatility. Then, we examine the impact of the COVID-19 deaths and the food price index on the REER volatility. In other word, the Russian Ukrainian war is measured by the monthly oil prices in the first model and by the food price index in the second model. Tables 5 and 6 show that the VIF values for both the first and the second models are less than 5.

Table 5. Multicollinearity statistics after adjustment-VIF/ First model.

Variables	VIF	1/VIF
Ldies	1.020	0.979
Lfpi	1.020	0.979
Mean VIF	1.020	

Table 6. Multicollinearity statistics after adjustment-VIF/ Second model.

Variables	VIF	1/VIF
Ldies	1.000	0.998
Lpo	1.000	0.998
Mean VIF	1.000	

- **Step four: Stationarity test**

At this level, we conduct a stationarity test on the different variables, which is a necessary requirement before performing thepanel ARDL model. For this purpose, we use the tests proposed by Im, Pesaran , & Shin (1997) (IPS) and Levin, Lin, and Chu (2002) (LLC) to test the null hypothesis of the unit root presence. The results in Table 7 show that variables "LvolREER" and "Ldies" are stationary at level, while "Lpo" and "Lfpi" are stationary at the first difference at a 1% significance level.

Table 7. Unit root test results.

Variables	IPS		LLC	
	At -level	At 1st difference	At -level	At 1st difference
LvolREER	-5.884***	-17.633***	-1.595*	-1.595***
Ldies	-19.600***	-24.786***	-18.684***	-27.975***
Lpo	0.031	-26.056***	-2.658***	-27.670***
Lfpi	1.524	-8.001***	-2.756***	-8.084***

Note: *** and * represent statistical significance at 1% and 10% respectively.

- **Step five: Panel ARDL specification**

In order to examine the effect of the COVID-19 pandemic and the Russian-Ukrainian war on the REER volatility, we apply the autoregressive distributed lags (ARDL) of the panel (Pesaran, Shin, & Smith, 2001; Pesaran, Shin, & Smith, 1999). The ARDL model is a combination of autoregressive models and stepped lag models. ARDLmodel can be used for panel data to analyze relationships between variables that may be stationary at the level or at the first difference. The ARDL panel models can be written as follows:

First model:

$$\Delta LvolREER_{it} = \alpha + \beta_1 LvolREER_{it-1} + \beta_2 Ldies_{it-1} + \beta_3 Lpo_{it-1} + \sum_{j=1} \gamma_{1,,} \Delta LvolREER_{i,t-j} + \sum^{q1} \gamma_{2,,} \Delta Ldies_{i,t-j} + \sum^{q2} \gamma_{3,i,j} \Delta Lpo_{i,t} + \varepsilon_{it}$$

Second model:

$$\Delta LvolREER_{it} = \alpha + \beta_1 LvolREER_{it-1} + \beta_2 Ldies_{it-1} + \beta_3 Lfpi_{it-1} + \sum_{j=1}^{p} \gamma_{1,,} \Delta LvolREER_{i,t-j} + \sum^{q1} \gamma_{2,,} \Delta Ldies_{i,t-j} + \sum^{q2} \gamma_{3,i,j} \Delta Lfpi_{i,t} + \varepsilon_{it}$$

Where α is the constant, $\gamma_1$to γ_3 are the short-term coefficients, and $\beta_1$to $\beta_3$are the long-term coefficients of LvolREER, Ldies, and Lpo for all the statistical individuals. If cointegration is established, then the panel error correction model equation can be written as follows:

First model:

$$\Delta LvolREER_{it} = \alpha_i + \sum_{j=1}^{p} \gamma_{1,i,j} \Delta LvolREER_{i,t-j} + \sum_{j=1}^{q1} \gamma_{1,i,j} \Delta Ldies_{i,t-j} + \sum_{j=1}^{q2} \gamma_{2,i,j} \Delta Lop_{i,t-j} + \theta_i ECM_{i,t} + \varepsilon_{it}$$

Second model:

$$\Delta LvolREER_{it} = \alpha_i + \sum_{j=1}^{p} \gamma_{1,i,j} \Delta LvolREER_{i,t-j} + \sum_{j=1}^{q_1} \gamma_{1,i,j} \Delta Ldies_{i,t-j} + \sum_{j=1}^{q_2} \gamma_{2,i,j} \Delta Lfpi_{i,t-j} + \theta_i ECM_{i,t} + \varepsilon_{it}$$

Where α is the constant, θ_i is the error correction coefficient, which measures the speed of adjustment from the short-term dynamics to the long-term equilibrium. The optimal lag of the Error Correction Model (ECM) to choose is the most common for each variable between the different individuals. In our case, the optimal lag, determined using Akaike's Information Criterion (AIC) and Bayesian information criterion (BIC), is ARDL (1,6,7).

- **Step six: Cointegration test**

Before estimating the panel error correction model, it is necessary to verify the presence of a long-term cointegration between the LvolREER and the independent variables by carrying out Kao (1999) panel cointegration test. This test includes the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests for the null hypothesis of non-cointegration, which can be expressed as H0:ρ=1 against the alternative hypothesis H1: ρ<1.

The results presented in Tables 8 and 9 show that the null hypothesis of no cointegration is rejected on the modified Dickey -Fuller, Dickey-Fuller, augmented Dickey-Fuller, unadjusted modified Dickey-Fuller, and unadjusted Dickey-Fuller tests at a 1% significance level. This suggests the presence of cointegration.

Table 8. Kao cointegration test results/ First model.

Statistical tests	T- statistic	P-value
Modified Dickey -Fuller t	-8.825	0.000
Dickey -Fuller t	-7.684	0.000
Augmented Dickey -Fuller t	-5.089	0.000
Unadjusted modified Dickey-Fuller t	-15.963	0.000
Unadjusted Dickey -Fuller t	-9.515	0.000

Table 9. Kao cointegration test results/ Second model.

Statistical tests	T- statistic	P-value
Modified Dickey -Fuller t	-9.135	0.000
Dickey -Fuller t	-7.872	0.000
Augmented Dickey -Fuller t	-5.304	0.000
Unadjusted modified Dickey-Fuller t	-16.149	0.000
Unadjusted Dickey -Fuller t	-9.630	0.000

- **Step seven: Causality test**

To examine the presence of long-term causality between the dependent and independent variables, we use the new testing approach proposed by Juodis, Karavias, & Sarafidis (2021) to test Granger's null hypothesis of no causality. This test offers improved size and performance by using a grouped estimator with a convergence rate (NT) ^ (1/2). It can also be used in multivariatesystems and remains valid against both homogeneous and heterogeneous alternatives.

Table 10. Results of the non-causality test of Juodis et al. (2021)/ First model.

JKS non- causality test		
Variables	**Coefficient**	**P-value**
HPJ Wald test	37.288	0.000
Results for the half-panel Jackknife estimator		
Variables	Coefficient	P-value
Ldies	-0.040	0.000
Lpo	-0.154	0.002

Table 11. Results of the non-causality test of Juodis et al. (2021)/ Second model.

JKS non- causality test		
Variables	**Coefficient**	**P-value**
HPJ Wald test	40.433	0.000
Results for the Half-Panel Jackknife estimator		
Variables	Coefficient	P-value
Ldies	-0.050	0.000
Lfpi	-0.064	0.590

As we can see in Tables 10 and 11, the null hypothesis state that the selected variables do not have a causal effect on LvolREER is rejected at a 1% significance level, with an optimal lag of 1 (according to AIC). The regression results indicate thatthe test outcome can be determined by LvolREER, Ldies and Lpo. This implies that the past values of these three variables contain information that helps predict LvolREER, beyond the information contained in its past values.

- **Step eight: Hausman Test**

In order to check whether there are significant differences between the *pooled mean group* (PMG), the *mean group* (MG) and the *dynamic fixed effect estimators* (DFE), we apply the Hausman test (Hausman, 1978). Firstly, we test the null hypothesis that the difference between PMG and MG is not significant, assuming both PMG and MG estimators are consistent. Subsequently, the test is re-applied to determine which estimator, PMG/MG or DFE, is more appropriate.

Table 12. Hausman test/ First model.

(MG-PMG)	(PMG-DFE)	
Chi2(8)	0.18	0.27
Prob >chi2	0.9126	0.8721

Table 13. Hausman test/ Second model.

(MG-PMG)	(PMG-DFE)	
Chi2(8)	1.81	0.29
Prob >chi2	0.4038	0.8663

Tables 12 and 13 present the results of the Hausman test, which indicate that the null hypothesis of homogeneity cannot be rejected. Therefore, the PMG estimator is considered superior to both the MG and DFE estimator. In other words, the PMG estimator is deemed the most efficient and suitable for interpretation.

4. Results and Discussion

4.1. Regression Results

Based on the panel ARDL model, Tables 14 and 15 show the short and long-term estimates of REER volatility. It should be noted that the monthly COVID-19 deaths and the price of oil barrels (or the monthly COVID-19 deaths and the food price index) serve as explanatory variables for REER volatility in the first (or second) model.

Table 14. Long- run results of the panel ARDL/ First model.

ARDL (1,6,7)				
Dependent variable: LvolREER				
Variable	**Coefficient**	**Standard error**	**T- statistic**	**P-value**
Ldies	0.0319	0.0112	2.85	0.004
Lpo	0.222	0.0412	5.39	0.000

Table 15. Long- run results of the panel ARDL/ First model.

ARDL (1,6,7)				
Dependent variable: LvolREER				
Variable	**Coefficient**	**Standard error**	**T- statistic**	**P-value**
Ldies	0.049	0.014	3.470	0.001
Lfpi	0.476	0.096	4.920	0.000

Table 16. Short- run results of the panel ARDL/ First model.

ARDL (1,6,7)				
Dependent variable: LvolREER				
Variable	**Coefficient**	**Standard error**	**T- statistic**	**P-value**
Δ Ldies (-1)	-0.1597	0.135	-1.19	0.236
Δ Ldies (-2)	0.1685	0.279	0.61	0.545
Δ Ldies (-3)	-0.1605	0.349	-0.46	0.645
Δ Ldies (-4)	0.074	0.244	0.30	0.762
Δ Ldies (-5)	-0.0204	0.106	-0.19	0.847
Δ Ldies (-6)	0.0034	0.024	0.14	0.887
Δ Lpo (-1)	-2.4004	0.872	-2.76	0.006
Δ Lpo (-2)	5.8802	2.374	2.48	0.013

ARDL (1,6,7)				
Dependent variable: LvolREER				
Variable	**Coefficient**	**Standard error**	**T- statistic**	**P-value**
Δ Lpo (-3)	-10.502	3.917	-2.68	0.007
Δ Lpo (-4)	10.785	3.9595	2.72	0.006
Δ Lpo (-5)	-6.706	2.5799	-2.60	0.009
Δ Lpo (-6)	2.3105	0.957	2.41	0.016
Δ Lpo (-7)	-0.3545	0.163	-2.19	0.029
ecm (-1)	-0.514	0.083	-6.24	0.000

Table 17. Short- run results of the panel (ARDL)/ Second model.

ARDL (1,6,7)				
Dependent variable: LvolREER				
Variable	**Coefficient**	**Standard error**	**T- statistic**	**P-value**
Δ Ldies (-1)	-0.258	0.1705	-1.51	0.131
Δ Ldies (-2)	0.415	0.327	1.27	0.204
Δ Ldies (-3)	-0.389	0.353	-1.10	0.270
Δ Ldies (-4)	0.234	0.264	0.89	0.375
Δ Ldies (-5)	-0.092	0.117	-0.79	0.432
Δ Ldies (-6)	0.0204	0.026	0.81	0.421
Δ Lfpi (-1)	-8.239	1.7102	-4.82	0.000
Δ Lfpi (-2)	26.4410	5.4808	4.83	0.000
Δ Lfpi (-3)	-47.808	10.4909	-4.56	0.000
Δ Lfpi (-4)	43.413	11.247	3.86	0.000
Δ Lfpi (-5)	-20.804	7.659	-2.72	0.007
Δ Lfpi (-6)	5.0187	3.099	1.62	0.105
Δ Lfpi (-7)	-0.557	0.559	-1.00	0.319
ecm (-1)	-0.535	0.086	-6.23	0.000

4.2. Discussion of the Results

The ARDL long-term results reported in Table 14 show that monthly COVID-19 deaths and monthly oil prices have a positive and significant effect on the REER volatility at a 1% significance level. In other words, an increase in terms of COVID-19 deaths and/or oil prices implies a more volatile REER. On the other hand, the ARDL short-term results, as shown in Table 16, show that monthly oil prices have a positive and significant effect on REERvolatility at both 1% and 5% significance levels, un to 7 lags.

Regarding the second model, the ARDL long-term results reported in Table 15 show that monthly COVID-19 deaths and monthly food price index have a positive and significant effect on the REER volatility at a 1% significance level. This implies that an increase in COVID-19 deaths and/or food price index leads to a more volatile REER. Additionally, the ARDL short-term results presented in Table 17 show that the food price index has a positive and significant impact on REER volatility at a 1% significance level, un to 5 lags.

The impact of the Russian-Ukrainian war, specifically oil prices, seems to be about seven times stronger than the COVID-19 deaths. Similarly, the impact of the Russian-Ukrainian war, specifically the food price index, seems to be about nine times stronger than the impact of COVID-19 deaths.

The ECM value reflects the extent to which short-term dynamics deviate from the long-term equilibrium. The significance level of 1% and the negative coefficient values for the first and the second cases, specifically -0.5134112 and -0.5344336, respectively, allow us to assess the usefulness and feasibility of the two models in the short term and interpret the results accordingly.

According to the short-term detailed results of the first model, the ECM values of Algeria, Brazil, Jordan, Turkey and the USA are negative but not significant. On the other hand, it appears from the detailed short-term results that there is a significant effect of the COVID-19 deaths on the REER volatility for Australia, Azerbaijan, Canada, India, Indonesia, Japan, Russia, South Africa, and Tunisia, with at least one lag showing significance at 1%, 5% or 10% level. Additionally, the results show the effect of the oil prices on the REER volatility is present for Azerbaijan, Canada, China, Denmark, Egypt, India, Indonesia, Japan, Mexico, Morocco, Russia, South Africa, the United Kingdom, and Tunisia, with at least one lag demonstrating significance.

Similarly, according to the detailed short-term results of the second model, the ECM values of Algeria, Azerbaijan, India, and Jordan are negative but not significant. On the other hand, the detailed short- term results reveal a significant effect of COVID-19 deaths on the REER volatility for Algeria,Australia, Bulgaria, Egypt, Indonesia, Japan, Morocco, Nigeria, Russia Federation, South Africa, The United Kingdom, Tunisia, and Turkey, with at least one lag showing significance at the 1%, 5% or 10% level. Furthermore, the results indicate that the effect of the food price index o REER volatility is present for Algeria, Australia, Bulgaria, Canada, China, Denmark, Indonesia, Japan, Mexico, Morocco, Nigeria, Russia Federation, South Africa, United Kingdom, Tunisia, and the United States, with at least one lag demonstrating significance at the 1%, 5% or 10% level.

In addition, our results regarding the effect of the COVID-19 pandemic, specifically COVID-19 deaths, on REER volatility are in line with the majority of previous studies such as Aquilante et al. (2022), Klinlampu et al. (2022), and Jamal and Bhat (2022). The increase in COVID-19 deaths is considered unfavorable, unpredictable, and exogenous news, thereby disturbing the evolution of different values in the capital markets, including the exchange rate, and undermining the expectations of different actors and stakeholders. Yet, our results regarding the effect of the Russian-Ukrainian war, namely oil prices and the food price index, on REER volatility are consistent with the studies by Sokhanvar and Bouri (2023) and Tiwari et al. (2022).

Similarly, the Russian-Ukrainian war effect on the REER volatility in the short term seems to be stronger andsignificant than the COVID-19 pandemic one for the two models. This observation holds true for each economy based on the detailed analysis. The high dependence of certain countries on imports of raw materials and energy has led to a significant increase in inflation rates and has further exacerbated the uncertain and unstable economic and financial context.

5. Conclusion

This study examines the effect of the COVID-19 pandemic and the Russian-Ukrainian war on REER volatility in 23 advanced, emerging, and developing economies during the period from January 2020 to October 2022. In this sense, we confirmed that COVID-19 deaths, oil prices, and the food price index have a significant positive impact on REER volatility at the 1% significance level. In the short term, there is a significant relationship at the 1% and 5% significance levels between the oil prices/food price index and REER volatility.

The global economy has experienced significant disruptions and faces heavy challenges that need to be addressed by various stakeholders such as governments, companies, and international institutions in response to an unprecedented health crisis that has affected everyone. Additionally, the Russo-Ukrainian war has further aggravated the situation and raised concerns about various economic recovery programs.

Ukraine and Russia are considered first-tier raw material-producing countries. The conflict between these two states has caused led to a rapid and significant increase in raw material prices (such as oil, gas, wheat, cereals, etc.) in the international market, consequently creating inflationary pressures in many economies. Moreover, Russia and Ukraine supply approximately 10% and 3% of the world's wheat production on average, respectively, and Russia is the world's leading exporter of natural gas (20% in 2019) and the world's second-largest oil exporter (11%) (*source: OECD*). As a result, decision-makers were faced with the dilemma of revitalizing the economy to address the effects of the health crisis while combating high inflation rates, primarily through interest rate increases.

In the face of this dilemma and the critical economic context, macroeconomic balances and various markets have been greatly destabilized. In this sense, we have confirmed econometrically that the COVID-19 pandemic and the Russian-Ukrainian war have intensified the volatile behavior of REER.

References

Aquilante, T., Di Pace, F., & Masolo, R. M. (2022). Exchange-rate and news: Evidence from the COVID pandemic. *Economics Letters*, *213*, 110390. https://doi.org/10.1016/j.econlet.2022.110390

Beirne, J., Renzhi, N., Sugandi, E., & Volz, U. (2021). COVID-19, asset markets and capital flows. *Pacific Economic Review*, *26*(4), 498-538. https://doi.org/10.1111/1468-0106.12368

El Rhadbane, A. B., & El Moudden, A. (2022). COVID-19 pandemic, real effective exchange rate and foreign direct investment inflows: Evidence from Morocco, Turkey and Egypt. *International Journal of Applied Economics, Finance and Accounting*, *12*(2), 38-51. https://doi.org/10.33094/ijaefa.v12i2.543

Feng, G.-F., Yang, H.-C., Gong, Q., & Chang, C.-P. (2021). What is the exchange rate volatility response to COVID-19 and government interventions? *Economic Analysis and Policy*, *69*, 705-719. https://doi.org/10.1016/j.eap.2021.01.018

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, *46*(6), 1251-1271.

Im, K., Pesaran , M., & Shin, Y. (1997). Testing for unit roots in heterogeneous panels. Department of Applied Economics, University of Cambridge, Cambridge.

Jamal, A., & Bhat, M. A. (2022). COVID-19 pandemic and the exchange rate movements: Evidence from six major COVID-19 hot spots. *Future Business Journal*, *8*(1), 1-11. https://doi.org/10.1186/s43093-022-00126-8

Juodis, A., Karavias, Y., & Sarafidis, V. (2021). A homogeneous approach to testing for Granger non-causality in heterogeneous panels. *Empirical Economics*, *60*(1), 93-112. https://doi.org/10.1007/s00181-020-01970-9

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, *90*(1), 1-44. https://doi.org/10.1016/s0304-4076(98)00023-2

Klinlampu , C., Rakpho , P., Tarapituxwong , S., & Yamaka , W. (2022). *How the exchange rate reacts to google trends during the COVID-19 pandemic?* Paper presented at the in International Econometric Conference of Vietnam, Springer, Cham.

Kohrt, L., Horky, F., & Fidrmuc, J. (2022). Exchange rates in emerging markets in the first wave of the Covid- 19 pandemic. *Eastern European Economics*, 1-22. https://doi.org/10.1080/00128775.2022.2074461

Levin, A., Lin, C.-F., & Chu, C.-S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, *108*(1), 1-24. https://doi.org/10.1016/s0304-4076(01)00098-7

Narayan, P. K. (2022). Understanding exchange rate shocks during COVID-19. *Finance Research Letters*, *45*, 102181. https://doi.org/10.1016/j.frl.2021.102181

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289-326. https://doi.org/10.1002/jae.616

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American statistical Association*, *94*(446), 621-634. https://doi.org/10.1080/01621459.1999.10474156

Sethi, M., Dash, S. R., Swain, R. K., & Das, S. (2021). Economic consequences of COVID-19 pandemic: An analysis of exchange rate behavior. *Organizations and Markets in Emerging Economies*, *12*(2), 258-284. https://doi.org/10.15388/omee.2021.12.56

Shahrier, N. A. (2022). Contagion effects in ASEAN-5 exchange rates during the COVID-19 pandemic. *The North American Journal of Economics and Finance*, *62*, 101707. https://doi.org/10.1016/j.najef.2022.101707

Sokhanvar, A., & Bouri, E. (2023). Commodity price shocks related to the war in Ukraine and exchange rates of commodity exporters and importers. *Borsa Istanbul Review*, *23*(1), 44-54. https://doi.org/10.1016/j.bir.2022.09.001

Tiwari, R., Singh, P., Kargeti, H., & Chand, K. (2022). Impact of Russia Ukraine war on exchange rate in India. *Available at SSRN 4281532*.

Zhou, H., Yu, M., Li, J., & Qin, Q. (2021). Rare disasters, exchange rates, and macroeconomic policy: Evidence from COVID-19. *Economics Letters*, *209*, 110099. https://doi.org/10.1016/j.econlet.2021.110099