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Volatility of Currencies during COVID-19 Pandemic

Master's Thesis

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We have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

Table of contents:

Abstract 3
Introduction 4
1. Literature review 6
2. Data and Methodology 10
3.Empirical study & results 14
Conclusion 29

Resume:

2019 aasta detsembris tuvastati koroona viirushaigus 2019 (COVID-19) ja kuu aja jooksul ilmnes selle haiguspuhang kogu maailmas, mõjutades enam kui 180 riiki. See haiguspuhang põhjustas erinevates riikides sulgemisi ja mõningaid olulisi ettevaatusabinõusid pandeemia ohjeldamiseks (Vinod & Sharma, 2021). Ilmselgelt poleks selline mõju finantsturgudest mööda läinud ja see on näidanud suurt volatiilsust peaaegu kõigis maailma valuutades.

Volatiilsus ise kui kontseptsioon näitab valuutaturu kõikumisi konkreetse valuutapaari puhul. On mitmeid aspekte, mis võivad põhjustada valuutapaari igapäevaselt kas lühi- või pikaajalist kõikumist. Need võivad olla poliitilised probleemid, nafta ja kaupade ning finantsvarade hinnamuutused ja palju muud. Kui aga toimub rahvusvaheline majanduslangus või mõjuvad katastroofid, võivad asjad muutuda hullemaks.

COVID-19 puhkemine oli ilmselgelt üks neist ülemaailmsetest probleemidest, mis põhjustas enamiku majanduste olukorra halvenemise, mis omakorda põhjustas otseselt või kaudselt valuutade kõikumisi maailma valuutaturgudel. Seda arvesse võttes analüüsime 8 erineva riigi valuutade tootlust euro suhtes kolmes ajadimensioonis: enne pandeemiat, pandeemia eelset ja pandeemia ajal, et näha, kuidas nende tootlus euro suhtes muutus ja kuidas pandeemia mõjus. mõju nende vahetuskursile.

Abstract

In December 2019, Coronavirus Disease 2019 (COVID-19) was identified and within a month its outbreak was seen across the world, with more than 180 countries being affected. This outbreak resulted in lockdowns and some major precautionary steps to contain the pandemic in various countries (Vinod & Sharma, 2021). This volume of impact obviously would not have passed by the financial markets and it's shown a lot of volatility in almost all the currencies in the entire world.

Volatility itself as a concept shows the fluctuations in foreign exchange market for a particular currency pair. There are numerous aspects which may lead a currency pair to fluctuate either in short-term or long-term time span on a daily basis. These may be political issues, oil and commodity and financial assets' price changes and many more. However, when there are international downturns or impactful disasters, then things may become worse.

COVID-19 breakout was obviously one of those worldwide problems which caused most of the economies to deteriorate which in turn directly or indirectly led to fluctuations in currencies in world foreign exchange markets. Taking that into account we analyze 8 different countries' currencies returns with respect to EUR in three time-dimensions: before pre-pandemic, pre-pandemic and during pandemic in order to see how their returns changed in relation to EUR and how the pandemic had an impact on their exchange rate.

Introduction

The growing financial interconnectivity has piqued the interest of market players and academic study, particularly in light of recent global economic events and financial instability. While the magnitude of return and volatility spillovers across global stock markets has received a lot of attention, less is known about foreign currency channels, particularly those between emerged and emerging nations. **Therefore, this study analyzes the volatility of currencies pair's in all before pre-pandemic, pre-pandemic and during pandemic**. Volatility is therefore a measure that is used to determine and predict the stability of a particular financial asset in any given financial market. Because of its implications on emerging countries, exchange rate volatility – defined as the exchange rate fluctuations over time – has dominated contemporary research in international finance. Concerns about exchange rate fluctuations have grown dramatically in both emerged and emerging economies, owing to their impact on exports (Wang and Barrett, 2007; Assery and Peel, 1991; Arize et al. 2000), employment growth (Belke and Setzer, 2003; Belke and Kaas, 2004) and trade (Doyle, 2001; Clark et al. 2004).

Foreign exchange markets are linked through trade and transactions involving products and services paid in foreign currency. Unexpected changes in the value of one country's currency can therefore hurt the trading partner. As Saunders and Cornett (2008) observed, the fact that many firms have globalized their operations means that unexpected fluctuations in the currency of foreign currencies can be detrimental to their profitability.

The globalization of the financial market means that the global economy is susceptible to shocks because of currency exchange volatility depending on the strength of the economies in question. Economic stability in emerged and emerging economies depends on how the countries manage their exchange rate volatility and their ability to curb drastic fluctuations in the value of their currency. This is because it is the value of currency that determines the country's trade level, employment, returns on investments and profitability of business enterprises.

Given the billions of dollars traded in worldwide financial markets on exchange rates, it's critical to thoroughly comprehend and analyze the possible spillovers of foreign currencies. This is a crucial consideration for investors when constructing their positions and portfolios. For others, the significance of foreign exchange market spillovers to global financial instability looked to be less concerning before the recent financial turbulence. In reality, stock price volatility (which has been thoroughly studied) is mostly explained by volatility in the foreign currency markets. There is no doubt that COVID-19 is not the only disease or world event which badly affected the currency market or other financial market instruments around the world. This epidemic has had a tremendous impact on the Chinese stock market, which is one of the worlds largest. (Apergis & Apergis, 2020). Hence, the motivation of this study is to analyze whether the pre-covid period was more volatile for currency market or the during covid period with respect to emerged and emerging economies and to see which of the time period amplified the herd behavior. Therefore, based on the above rationale the precise aim of this study is to analyze the excess volatility of financial instruments, specifically currency exchange in terms of emerged and emerging markets/ economies.

This paper analyzes excess currency exchange volatility in eight emerged and emerging economies that are among the leading economies in the world. These are China, Turkey, Ukraine, Switzerland, Brazil, the UK, Japan and the USA. The selected countries combined have a great impact on the global economy. Most of the transactions in the global markets are denominated in their currencies. Currency exchange volatility is therefore an issue of concern for not only policy makers but also local business enterprises, domestic consumers in addition to foreign investors.

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is employed to calculate the measure of excess volatility. This is in contrast to several previous studies that used unconditional measures of volatility, such as variance or standard deviation, and failed to notice that there are fascinating patterns in volatility research, such as time-varying and clustering features. With this study we are trying to find how COVID-19 affected the FX returns in relation to EUR of 8 economies. We are hypothesizing that the emerging economy currency exchange rates were more volatile than the exchange rates of emerged economies currencies. This study is divided into following sections which are as follows: Abstract, Introduction, Chapter 1: Literature review, Chapter 2: Data and Methodology, Chapter 3: Empirical Study, and Conclusion.

1. LITERATURE REVIEW

Volatility in the exchange rate has attracted the interest of different scholars and policymakers as the uncertainty that accompanies the projected revenue in relation to cost has rendered many business activities and transactions to become uneconomic (Chen, Du, & Hu, 2020; Feng et al., 2021). This impact is even more pronounced when either the cost or revenue is not in the same currency. The volatility in the exchange rate depicts the degree to which the exchange rate changes over time. It also refers to the risk that is associated with exchange rate unexpected movements.

1.1 Various tools and techniques to measure volatility in exchange rates

Measuring volatility has been one of the major focuses in the discipline of finance. The spillover effect associated with volatility such as reduction in capital market confidence, determining the stand of firms in bankruptcy, hedging technique and a crucial tool in establishing bid-ask spread makes it an important concept to focus on. In measuring volatility, the most common approach is to take the standard deviation of the returns. However, when the focus of measuring volatility is the uncertainty associated with it, the root mean square percentage error is employed for this. This measure is well known for predicting errors.

According to previous research, the financial market is assumed to be predictable especially when the effects of ARCH are present. This is a very important finding as it has a germane implication to risk-averse investors who can stay safe by reducing the risk they are exposed to by investing only in assets whose volatilities are much predicted. More so, there has been a sharp deviation from what is considered the weakness of former models which considered that the volatility is constant over a period of time (Serenis & Tsounis, 2012). In finding the best volatility forecast, some of the models that are used are autoregressive conditional heteroskedasticity (ARCH) model, generalized autoregressive conditional heteroskedasticity (GARCH) model, exponential autoregressive conditional heteroskedasticity (EGARCH) model, and the Taylor-Schwert model among others (Daly, 2008). These models are considered to be supreme because of the time-variant consideration that is factored into these measures. They maintain the assumption that over time, volatility changes.

1.2 Factors affecting the volatility of exchange rates

As one of the metrics employed in determining the economic health of a nation, the exchange rate demands the utmost attention to present the economy favorably to attract benefits associated with foreign relationships. The level of stability obtainable in any economy is also intertwined with the volatility of her foreign exchange rate which makes the movement in the rate be closely monitored. Basically, changes in the market forces via the demand and supply of currencies may bring about the daily fluctuation in the exchange rate. However, some other factors drive the variation in the foreign exchange rate. Knowing these factors as an individual can help you understand what you get when you exchange one currency for another. More so, these factors affect the foreign exchange rate at the global level (You & Liu, 2020).

1.2.1: Economic Shocks that affect Volatility

1. Inflation: The changes in the foreign exchange rate is related to inflation in the market. Inflation in this scenario is the relative purchasing power that a currency commands in relation to other currencies. For instance, a pack of apples might cost ten units of a country's currency while buying the same pack of apples in another currency will cost up to a thousand units of the other country’s currency due to higher inflation. The aforementioned scenario of difference in inflation serves as the background of why the purchasing power of different currencies differs. However, research has shown that countries that are experiencing a low level of inflation do have stronger currencies which have a high purchasing power compared to currencies with higher inflation rates (Ahmend, Aizenman, & Jinjarak, 2021).

2. Demand Pull Theory: According to (Arghyrou & Pourpourides, 2016), (Ebiringa & Anyaogu , 2014), and Nucu (2011), an increase in inflation reduces the value of the home nation, resulting in an increase in the exchange rate volatility . The currency rate is negatively affected by demand pull inflation (Necșulescu and Erbanescu 2013; Namjour et al. 2014). However, Abbas et al. (2012) studied the currency rate of African countries and discovered that inflation had a little impact on the exchange rate.

3. Speculation: The confidence that traders have in a particular currency is another factor that influences the volatility of the currency. This will bring about speculating about the currencies and such changes have been shown by research to be irrational and short-lived. For instance, when economic growth and trade are considered to be affected by any shock, trades might devalue the currency based on the happening. In a reverse manner, when economic news tends to be favorable to a particular currency, traders may make a move that will buy the currency even though the news may not contribute to movement in fundamentals of the currency (Kilicarslan, 2018).

4. Interest rate: The changes in interest rate affects exchange rate and currency value. One major reason for this is that exchange rate and inflation are tightly tied to the interest rate. The central bank which is the apex bank in a country uses the interest rate as an instrument to regulate inflation within the economy. When a country has a higher interest rate, the currency rate is bolstered as a result of the foreign capital inflow that it attracts. This can only be a short term move as if the interest rate remained high for so long, it might cause inflationary pressure in the country. The apex banks are saddled with the responsibilities of balancing the drawbacks and benefits (Feng et al., 2021).

5. Public debt: Deficit financing has been employed by many countries to finance their budgets. Public debt is also referred to as national debt or government debt and it is owned by the central government. One key way in which public debt influences the movement of the foreign exchange rate is that if it is used to finance economic growth and it turns out to outpace economic growth, price stability will be affected. This will in turn discourage the inflow of foreign investment into the country which will lead to devaluation of the currency. The problem can be further compounded when the government embarks on printing money to settle the debt (Ahmend, Aizenman, & Jinjarak,2021).

1.2.2: Non-Economic Shocks that affect Volatility

1. **Political (in)stability:** The level of political stability that a country has is positively related to the level of foreign direct investment that flows into the country. When a country has a higher political level of stability, the country's currency will be more strengthened as a result of

the foreign investment it attracts. The impact of political tension also spilled over to financial policies and local economic drivers as well. These will have a long-term effect on the exchange rate of the country be it positive or reverse (Muhammad, Azu, & Oko, 2018).

2. COVID-19: Cepoi (2020) examined fresh empirical data on the association between COVID-19 news and stock market/currency market performance in the pandemic's six worst-affected nations. The research revealed that the stock market is too connected to COVID-19 information using a quantitative regression model in a panel structure. Furthermore, the findings indicated that effective communication channels are required to mitigate COVID-19 financial shocks. The similar effect can be found in the Corruption Perceptions Index, which demonstrates that the more institutions involved with COVID-19 news, the poorer the stock market/currency market performance, especially during the recovery phase.

1.3 Review of previous studies (The impacts of different economic shocks on volatility of exchange rates)

Several studies have examined the impact that different economic shocks that occurred at one time or the other in a country have on the volatility of their exchange rate. One of the aforementioned is the work of Kuncoro (2020) who examined volatility of exchange rate and interest rate policy using Indonesia as the case study. The study attempts to explain the controversy that surrounds the phenomenon of how the volatility of the exchange rate has been influenced by the inflation targeting that is adopted. Monthly data set of Indonesia ranging from the period of July 2005 to July 2016 was employed to test the hypothesis using the autoregressive distributed lag (ARDL) model. The result revealed that foreign exchange intervention and interest rate policy did not reduce the volatility of the exchange rate.

The findings further revealed that neglecting the external value of a currency by placing much emphasis on the stability of the domestic currency also led to a rise in the volatility of the exchange rate. Lastly, the study found that through the signaling effect, the central banks are key based on the inflation targeting policy.

Stancik (2006) examined exchange rate volatility determinants using the new EU members as the case study. The research employed a threshold autoregressive conditional heteroskedasticity (TARCH) model in modeling volatility in the exchange rate. The findings revealed the impact of news has a significant effect on volatility. The impact of the exchange rate system was also considered in the study and the result revealed that a flexible regime is associated with a higher level of volatility. The effect of economic openness on exchange rate volatility was found to be calm and it was noted that the degree of the effects across the countries is not constant.

Our **CERCS** code is S180.

2. Data and Methodology

2.1 Data Description

The dataset consist of daily prices of the exchange rate pairs against the EUR for 4 emerging and 4 emerged economies during the pandemic, pre-pandemic and before pre-pandemic period (China - EUR/CHY, Brazil – EUR/BRL, Turkey – EUR/TRY, Ukraine - EUR/UAH, Switzerland - EUR/CHF, UK- EUR/GBP Japan – EUR/JPY and the United States – EUR/USD). Dataset during the pandemic covers the period from March 4, 2020 to February 22 (short timeframe dataset), 2022 whilst the dataset for pre-pandemic covers the period from March 1, 2018 to February 28, 2020 and dataset for before pre-pandemic period covers the period from April, 2013 to March 1, 2018 (long timeframe dataset). These countries are considered because they have not been altogether at the center of the researchers' interest within a recent period after the crisis. A full sample includes 4,168 observations for the eight economies within pre-pandemic and pandemic period whereas the sample for before pre-pandemic period has 10440 observations. Table 1 presents descriptive statistics of each currency exchange with the EUR returns according to trading days to get a better insight of weekday effects for all emerging markets and emerged markets together. We have gathered the data from "Thomson Reuters Global Financials Index" and a few other sources such as "Yahoo Finance" and "Investing.com". Our methodology considers the best two econometric models in volatility measurements which are ARCH and GARCH models.

2.2 Auto Regressive Conditional Heteroskedasticity (ARCH) and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)

The examination of monetary information has gotten extensive consideration in the writing in the course of the most recent twenty years (carrera and vuletin, 2002; schnabl, 2007; Gadnanecz and Mehrotra, 2013). A few models have been recommended for capturing specific elements of financial information, and the vast majority of these models have the property that the conditional variance relies upon the past. Notable and as often as possible applied models to appraise estimate exchange rate volatility are the autoregressive conditional heteroscedastic (ARCH) model, progressed by Engle, R.F. (1982) and generalized autoregressive conditional heteroskedastic (GARCH) model, developed independently by Bollerslev Bollerslev, T. (1986) and Taylor Taylor, S.J. (1986). These models are applied to represent attributes of volatility in exchange rate such as dynamic conditional heteroscedasticity. Specifically, this class of models has been utilized to conjecture variances in products, securities and exchange rates.

Henceforth, The Autoregressive Conditional heteroskedasticity (ARCH) financial models is a predominant framework utilized in instability assessment in econometric discourse.. ARCH assumes that conditional variance h_t(equation 1) is a function of squared random variable occurrences taken for the specific time window of length q:

$$h_t = \alpha_0 + \sum_{j-1}^{q} \alpha_j \varepsilon_{t-j}^2$$

Where y_t is an observed random variables,

$$\varepsilon_t = y_t - E\left(y_t\right) = z_t h_t^{\frac{1}{2}},\ \alpha_0 > 0,\ a_j \geq 0,\ j = 1, \ldots 1 - q,\ \text{and } a_j > 0.$$

In the present time a generalized form (Generalized Autoregressive Conditional heteroskedasticity) GARCH process has become prevalent in econometric modeling and financial literature. It is an extended specification of conditional variance h_t, which is now also dependent on linearly from both variance and its own lags of orders 1 to p (equation 2)

$$h_t = \alpha_0 + \sum_{j-1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j-1}^{p} \beta_j h_{t-1}$$

From inception in 1986 by Bollerslev (1986) diverse upgrade have been made to GARCH- nonlinear GARCH models like smooth transition GARCH and threshold GARCH, time-varying GARCH, Markov-switching GARCH, integrated GARCH, exponential and multivariate models of generalized conditional heteroskedasticity, which are covered in Terasvirta (2009). However, according to the research conducted by Terasvirta (2009), the most popular model of GARCH is a simple GARCH(1,1), which only looks at the first lags of ε and h. Coefficients of regressors and α_i and β_i can be estimated using maximum likelihood method and sufficient condition for the GARCH process to be weakly stationary is

$$\sum \alpha_i + \sum \beta_i < 1,$$

, as it is stated in Terasvirta (2009).

GARCH models have both strong sides and weak points. Although GARCH has proved to be robust for short-term conditional volatility modeling, it assumes a symmetrical effect of both positive and negative innovations in time series, which does not align with empirical observations as it is written in Engle and Patton (2007). These authors also show GARCH dependency on data points frequency in terms of the model specification when the same asset is studied, but time steps vary. What is more, Engle and Patton (2007) focus their attention on the fact that even if a number of assets' conditional volatilities tend to be described by GARCH model precisely, portfolios constituted of the same assets are not necessarily described by this model properly. Finally, the idea of volatility persistence described earlier is violated by GARCH unless the p parameter is large enough. Although several analyses of exchange rate volatility in the finance and economic literature are conducted by means of autoregressive conditional heteroskedasticity (ARCH) or generalized ARCH (GARCH) models. However, according to

Humilton and Susmel (1994) many of such models have the tendency of predicting a higher volatility than they are in their actual volatility rates, and their predictive performance is considerably low. Hence, Diebold and Lamoureux and Lastapes have argued that this is due to structural change inherent in the ARCH process. Hence, Hamilton and Susmel(1994) for this purpose developed the Markov-switching ARCH (MS-ARCH or SWARCH) model to overcome the reliability problem of parameter estimates that do not allow for a regime change. However, with the adoption of GARCH for our model, we overcome the problem associated with ARCH.

2.3 Review of previous studies (The impacts of different economic shocks on volatility of exchange rates)

Several studies have examined the impact that different economic shocks that occurred at one time or the other in a country have on the volatility of their exchange rate. One of the aforementioned is the work of Kuncoro (2020) who examined volatility of exchange rate and interest rate policy using Indonesia as the case study. The study attempts to explain the controversy that surrounds the phenomenon of how the volatility of the exchange rate has been influenced by the inflation targeting that is adopted. Monthly data set of Indonesia ranging from the period of July 2005 to July 2016 was employed to test the hypothesis. Using the autoregressive distributed lag (ARDL) model. The result revealed that foreign exchange intervention and interest rate policy did not reduce the volatility of the exchange rate. The findings further revealed that neglecting the external value of a currency by placing much emphasis on the stability of the domestic currency also led to a rise in the volatility of the exchange rate. Lastly, the study found that through the signaling effect, the central banks are key based on the inflation targeting policy.

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3.Empirical study & results

3.1 Analysis Based on the Short Pre-pandemic Data

Table 1: Descriptive Statistic Pre-pandemic

	Emerged Economies				Emerging Economies			
	EUR_CHF	EURGBP	EURJPY	EURUSD	EUR_BRL	EUR_CNY	EUR_UAH	EUR_TRY
Mean	1.126182	0.877919	125.1075	1.140325	4.418854	7.754777	29.88706	6.182701
Median	1.129230	0.879665	125.1185	1.132452	4.402950	7.767650	30.50810	6.306250
Maximum	1.199260	0.932120	133.1160	1.245501	4.933800	8.083200	33.04530	7.853300
Minimum	1.061030	0.829790	116.1610	1.078772	3.983800	7.405900	25.74680	4.668500
Std. Dev.	0.031868	0.019171	4.432724	0.036505	0.185141	0.135694	2.097939	0.616801
Skewness	0.102793	-0.148779	-0.027549	1.124031	0.241620	-0.196794	-0.407593	-0.469176
Kurtosis	2.524287	2.642494	1.752093	3.846027	2.792989	2.402844	1.838058	3.280149
Jarque-Bera	5.841353	4.705653	33.93667	125.4875	6.011137	11.12528	43.81839	20.85795
Probability	0.053897	0.095100	0.000000	0.000000	0.049511	0.003839	0.000000	0.000030
Sum	587.8671	458.2738	65306.14	595.2496	2306.642	4047.994	15601.05	3227.370
Sum Sq. Dev.	0.529105	0.191487	10237.15	0.694304	17.85833	9.593032	2293.102	198.2113
Observations	522	522	522	522	522	522	522	522

The descriptive statistics of the variables pre-pandemic show that the means and medians can be found between maximum and minimums values. This suggests the tendency of variables being normally distributed. EUR/BRL has a mean of 4.418854 which falls between a minimum value of 3.9838 and maximum value of 4.9338. A standard deviation of 0.185141 signifies a small deviation from the mean value which is suggestive of a normal distribution before the pandemic outbreak. The EUR/BRL skewness shows it is positive. The kurtosis statistic shows that EUR/BRL is platykurtic with the value of 2.402844. This suggests that the distribution is flat relative to the normal distribution. Jarque-bera statistic accepted the null hypothesis of normal distribution for EUR/BRL, at five percent (5%) critical value. EUR/CNY has a mean of 7.754777 which falls between a minimum value of 7.4059 and maximum value of 8.0832. It has a standard deviation of 0.135694 which depicts a small deviation from the mean value and further indicates an attribute of normal distribution before the pandemic outbreak for the currency pair. The EUR/CNY skewness shows it is negative. The kurtosis statistic shows that EUR/CNY is platykurtic with the value of 2.402844. This suggests that the distribution is flat relative to the normal distribution. Jarque-bera statistic accepted the null hypothesis of normal distribution for EUR/BRL, at five percent (5%) critical value while the null hypotheses for the normal distribution of the variables were rejected at the same level of significance based on a p-value of 0.003839. EUR/JPY has a mean of 125.1075 which also falls between a minimum value of 116.161 and a maximum value of 133.116. However, a standard deviation of 4.432724 appears to be larger compared with other currency pairs. This is also evidenced during the pandemic for the EUR/JPY. The EUR/CNY skewness shows it is negative. The kurtosis statistic shows that EUR/JPY is platykurtic with the value of 1.752093. This suggests that the distribution is flat relative to the normal distribution. Jarque-bera statistic accepted the null hypothesis of normal distribution for EUR/BRL, at five percent (5%) critical value while the null hypotheses for the normal distribution of the variables were rejected at the same level of significance based on a p-value of 0.00000. Jarque-bera statistic accepted the null hypothesis of normal distribution for other pairs at less than 5% significant level but rejected it for EUR/GBP.

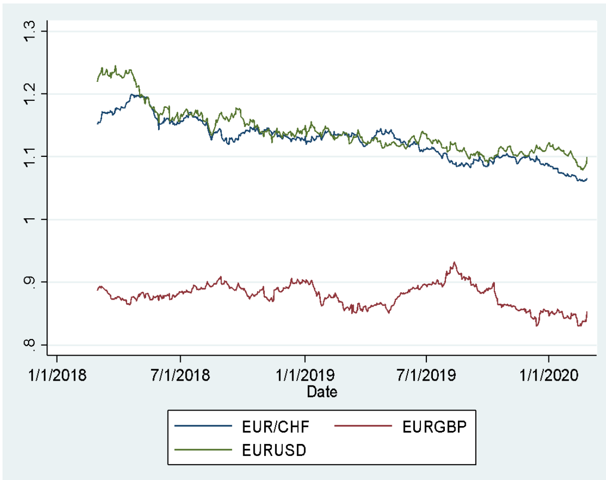
Table 2 Descriptive Statistics of Currency Pair During Pandemic

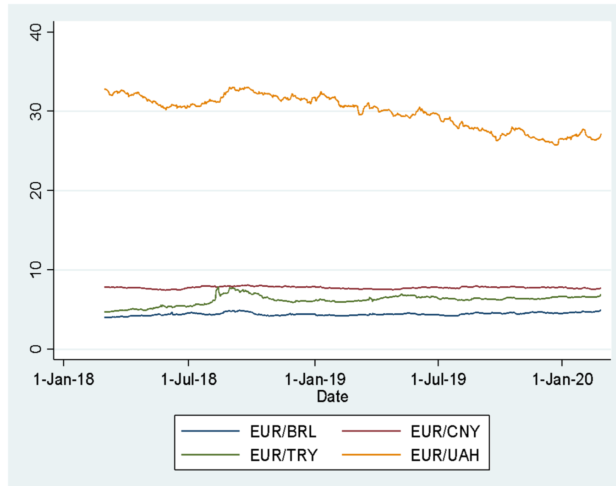
	Emerged Economies				Emerging Economies			
	EURCHF	EURGBP	EURJPY	EURUSD	EUR_BRL	EUR_CHY	EUR_TRY	EUR_UAH
Mean	1.073676	0.874009	126.6052	1.165240	6.253258	7.714206	9.941618	31.96370
Median	1.076215	0.868280	127.9420	1.176471	6.302950	7.772650	9.479350	32.25460
Maximum	1.112110	0.942300	133.9830	1.233776	6.958400	8.301700	18.44550	34.94520
Minimum	1.033730	0.831800	114.6970	1.065848	4.980500	7.082000	6.763500	27.62350
Std. Dev.	0.018418	0.024798	4.683540	0.039508	0.325063	0.274328	2.337224	1.593096
Skewness	-0.209776	0.205956	-0.665242	-0.497085	-0.850213	-0.551024	1.366968	-0.359742
Kurtosis	2.414356	1.813113	2.501219	2.336231	4.002800	2.734128	4.269001	2.146720
Jarque-Bera	11.24506	34.19806	43.74431	30.96085	84.43614	27.84592	196.8368	26.99114
Probability	0.003615	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	0.000001
Sum	558.3113	454.4847	65834.69	605.9247	3251.694	4011.387	5169.641	16621.13
Sum Sq. Dev.	0.176053	0.319143	11384.55	0.810112	54.84074	39.05790	2835.099	1317.199
Observations	520	520	520	520	520	520	520	520

The descriptive statistics of the variables during pandemic show that the means and medians can be found between maximum and minimums values. This suggests the tendency of variables being normally distributed. EUR/BRL has a mean of 6.253258 which falls between a minimum value of 4.980500 and maximum value of 6.958400. A standard deviation of 0.325063 signifies a small deviation from the mean value which is suggestive of a normal distribution during the pandemic outbreak. The EUR/BRL skewness shows it is negative with the value of -0.850213. The kurtosis statistic shows that EUR/BRL is leptokurtic with the value of 4.002800 which is higher than 3 for normal distribution. This suggests that the distribution is high relative to the normal distribution. Jarque-bera statistic accepted the null hypothesis of normal distribution for EUR/BRL, at five percent (5%) critical value. EUR/CNY has a mean of 7.714206 which falls between a minimum value of 7.082000 and maximum value of 8.301700. it has a standard deviation of 0.274328 which depicts a small deviation from the mean value and further indicate an attribute of normal distribution during the pandemic. The EUR/CNY skewness shows it is negative with a value of -0.551024. The Kurtosis Statistics shows that EUR/CNY is platykurtic with the value of 2.402844. This suggests that the distribution is flat relative to the normal distribution. Jarque-bera statistic accepted the null hypothesis of normal distribution for EUR/BRL, at five percent (5%) critical value while the null hypotheses for the normal distribution of the variables were rejected at the same level of significance based on a p-value of 0.000001. EUR/JPY has a mean of 126.6052 which also falls between a minimum value of 114.6970 and a maximum value of 133.9830. However, a standard deviation of 4.683540 appears to be larger compared with other currency pairs. The EUR/JPY skewness shows it is negative. The kurtosis statistic shows that EUR/JPY is platykurtic with the value of 1.813113. This suggests that the distribution is flat relative to the normal distribution. Jarque-bera statistic accepted the null hypothesis of normal distribution for EUR/JPY , at five percent (5%) critical value while the null hypotheses for the normal distribution of the variables were rejected at the same level of significance based on a p-value of 0.00000. Jarque-bera statistic accepted the null hypothesis of normal distribution for other pairs at less than 5% significant level.

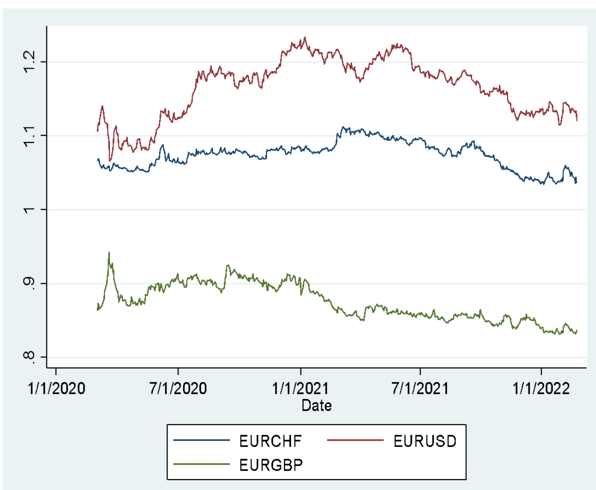
3.1.1 Stationary Test and Data Visualization

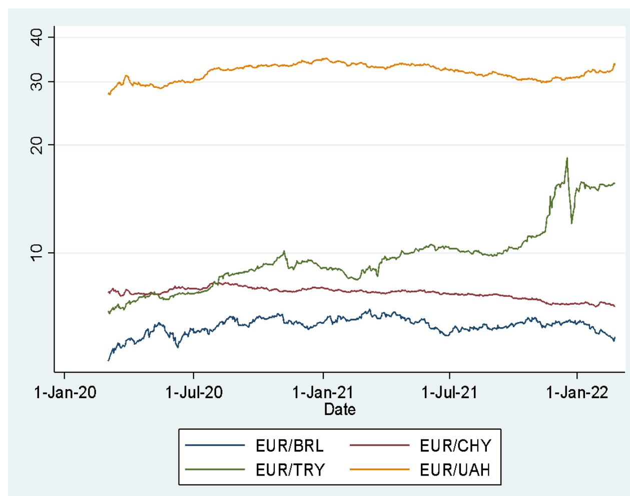
Pre-pandemic Period





During Pandemic





Source: Author's Computation 2022

Major step toward our model estimation and to determine the stationarity of our variables is to plot the graph of the series for visualization. One of the stylized facts of the GARCH model similar to the ARCH is that its evidence shows volatility clustering of the series. One obvious fact with the EUR/BRL, EUR/TRY and EUR/UAH currency pair pre-pandemic period is the mean reversion as observed in the graphical plots above. GARCH models were among the first models to take into account the volatility clustering phenomenon. In a GARCH(1,1) model the (squared) volatility depends on last periods volatility.

Unpredictability clustering implies that enormous changes will more often than not be trailed by huge changes, of one or the other sign, or little changes will quite often be trailed by little changes. The GARCH plot created in the mid 1980s is instrumental in promoting this reality in econometric models. By allowing the conditional variance to rely upon the past square of innovations. It straightforwardly catches the impact that once the market is vigorously unstable it is bound to remain so rather than to quiet down as well as the other way around (De Vries, G.C. and Leuve, K.U. (1994)). In this way, GARCH models not just gauge the way for the time-varying conditional variance of the exchange rate, yet additionally enables us to catch the suitable contingent instability present in the exchange rate. As evidenced from the above exchange rates as captured in the graph, the variance cluttering effect would indicate a stability of pre-pandemic currency pair by mere visualization.

However, the currency pair for developed countries and currency pairs during the pandemic for both emerged and emerging countries show some instability. Hence, leading before we estimate ARCH and GARCH model there is a need to conduct a unit root test as presented below:

3.1.2 Unit Root Test

Table 3. Stationarity Test

	Prepandemic		During Pandemic	
Variable	**T-Statistic**	**Order of Integration**	**T-Statistic**	**Order of Integration**
EUR/CHF	-22.73970**	I(1)	-1.324134**	I(1)
EUR/GBP	-23.67741**	I(1)	-4.169840**	I(0)
EUR/JPY	-23.89439**	I(1)	-23.01149**	I(1)
EUR/USD	-23.40842**	I(1)	-21.65305**	I(1)
EUR/BRL	-25.73003**	I(1)	-3.516706*	I(0)
EUR/CNY	-23.61505**	I(1)	-24.61620**	I(1)
EUR/TRY	-16.30475**	I(1)	-20.17579**	I(1)
EUR/USD	-21.84028**	I(1)	-14.05937**	I(1)

Source: Author's Computation 2022

**** significant at 5% level of significance * significant at 1% level of significance**

The new current developments in time series modeling, unit root tests of the time series properties of the data are studied to ascertain the order of integration of the variables used in the model. A series is said to be stationary at level if the null hypothesis is accepted, otherwise reject the stationarity test at level and proceed to the first difference. The Augmented Dickey Fuller root test was carried out. The results as presented in Table 2 clearly reveals that prepandemic all the currency pairs namely EUR/CHF, EUR/GBP, EUR/JPY, EUR/USD, EUR/BRL, EUR/CNY, EUR/TRY and EUR/USD only became stationary after first differencing, that is I (1). Similarly all the currency pairs only become stationary at first differencing during the pandemic except for EUR/GBP and EUR/BRL which were stationary at level. Going forward, we proceed to conduct the estimate the ARCH and GARCH model

3.1.3 ARCH and GARCH Estimation

The parametric measure of exchange rate volatility estimates volatility in exchange rate using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. This is distinct from some past studies that employed traditional measures of volatility, represented by variance or standard deviation that are unconditional and do not recognize that there are interesting patterns in volatility study, time-varying and clustering properties. This lends credence to the choice of GARCH model presented in the table below. The table 4.2 below presents the parameter of estimates and their corresponding p-values for emerged and emerging economies in two separate periods: pandemic and during pandemic using the GARCH (1, 1) model for this exchange rate study (The original table from STATA is contained in the Appendices).

Table 4: Summary of the ARCH and GARCH Estimation

	Pre-Pandemic		During Pandemic	
	Emerging	Emerged	Emerging	Emerged
Price				
Constant	7.722897**	1.128981**	7.766993**	1.08058***
ARCH				
L1	1.015027**	0.9961575*	0.9990746***	0.9970402***
GARCH				
L1	-3.52E-06***	-3.59E-10***	0.995	4.44E-10
Constant	0.0008324*	0.0000107**	0.0012795	7.46E-06

Source: Author's Computation 2022. **Significant at 1% level, ** Significant at 5% level, *** Significant at 10% level**

The coefficients of the constant variance term, the ARCH, are positive both before the pandemic and during the pandemic for both emerging and emerged economies. The coefficients of the constant terms and GARCH were only positive and significant during the pandemic, the time varying volatility includes a constant and a component which depends on past errors. As a proof that this model satisfies stability conditions, the summation of the coefficient of GARCH term and the constant term is less than one, except for emerging .The statistically significant positive coefficient of the GARCH for during the pandemic is not surprising. For the variance equation, pre-pandemic period, the coefficient of the ARCH effect is positive for both emerging and emerged economies. Both were positive and significant at less than 5% level of significance. This depicts the presence of high volatility clustering of exchange rate before the outbreak of pandemic in both emerged and emerging economies. However, from the data the ARCH coefficient of 1.015027 is for emerging economies is higher than ARCH coefficient value of 0.9961575 in emerged economies. Comparatively during the pandemic, the ARCH coefficient still possessed the positive sign but was not significant. Hence, it can be deduced that the pandemic had a significant effect on the volatility clustering character of exchange rate for both emerging and emerged economies.

On the GARCH coefficients, during the pandemic, $\beta\ represented\ by\ L1\ in\ the\ table$ for emerging economies was 0.995 and statistically significant at less than 5% level of significance. This depicts a very high exchange rate volatility traceable to the effect of the pandemic for emerging economies while during the same period for the emerged or developed economies β was 4.44E-10 and statistically significant at less than 5% level of significance. This indicates a very low volatility in exchange rate for emerged economies. It can therefore be inferred that exchange rate volatility subsequent to the outbreak of the coronal virus pandemic was significantly higher in emerging economies compared with emerging economies. These findings corroborate with Feng et al., (2021) study on what is the exchange rate volatility response to COVID-19 using 20 sampled economies evidenced that the increase in the percentage of biweekly confirmed cases has indeed boosted exchange rate volatility at a 5% significance level. His study further revealed that the various policies adopted by governments in response to the pandemic, such as closing schools, restrictions on internal movements, and public information campaigns also inhibit exchange rate volatility. Going further, in view of the fact that China experienced a relatively serious pandemic in the early stage, and the government has adopted more stringent measures to almost shut down the Chinese economy, which is not experienced by other countries. Therefore, in order to ensure the robustness of the above conclusions, this study now excludes the Chinese samples and performs a subsample regression again. The regression results are still consistent with the above findings. According to the study of Aslam et al. (2020), the Australian dollar, Japan Yen, and Euro were the currencies whose efficiency levels decreased during the pandemic. Similarly, Rakshit, B., & Neog, Y. (2021) finding in their study on the effects of the COVID-19 pandemic on stock market returns and volatilities: Evidence from selected emerging economies showed that exchange rate volatility exerts a negative and significant effect on the market returns in Brazil (BOVESPA), Chile (S&P CLX IPSA), India (SENSEX), Mexico (S&P BMV IPC) and Russia (MOEX) during the coronavirus pandemic, which is likewise evidence in the result we obtained for this study. Furthermore, Rakshit, B., & Neog, Y. (2021) study opined that the effect of oil price returns, the authors find a positive relationship between oil price and stock market returns across all the economies in the study. The market returns of Russia, India, Brazil and Peru appeared more volatile during the pandemic than the GFC period.

However before the pandemic the GARCH coefficient $(L1\ )\ specified\ as$ β in the model was not significant for both emerging and emerged economies considered in our panel data. The GARCH coefficient for emerging economies was -3.52E-06 and statistically insignificant while the GARCH coefficient for emerged economies was -3.59E-10 and also statistically insignificant. According to Mensi et al. (2020). Before the pandemic, the oil market was more efficient during upward trends. In contrast, the gold market was more efficient during downward trends. During the pandemic, these were reversed. It can be said that gold and oil markets became more speculative and COVID-19 has a negative impact on these market efficiency. Rui Dias and Santos (2021) adopted an econophysis approach to determine the impact of COVID-19 on exchange rate volatility on nine currencies based on data obtained between 2019 and 2020. Result obtained based on analysis using different approaches revealed that the impact of the global pandemic created long memories in international foreign exchange markets for typical currency pair of developing countries such as with US-MYR (US-Malaysia) US-PHP (USPhilippines) and US-THB (US-THAILAND), above the pairs with advanced countries such as with US-EUR (US-ZONE Europe), US-JPY (US-Japan), US-SGD (US-Singapore), US-CHF (USSwitzerland), US-GBP (US-UK). Ethan etal (2020) argued that the stability in the USD despite the pandemic is strongly strengthened by expectations that in the years to come there will be a significant binding in the zero bound for advanced economies.

3.2 Analysis Based on the Long Pre-pandemic Data

Table 5: Summary Statistics

	Emerging Countries			
	EUR/TRY	**EUR/UAH**	**EUR/CNY**	**EUR/BRL**
Obs	1305	1305	1305	1305
Sum of Wgt.	1305	1305	1305	1305
Mean	3.342786	23.34391	7.637897	3.523268
Std. Dev.	.6423803	7.458248	.4993123	.4418534
Variance	.4126525	55.62546	.2493128	.1952344
Skewness	.8646271	-.4869149	.1097712	.3233281
Kurtosis	2.790556	1.840157	2.180804	2.233528
	Emerged Countries			
	EUR/CHF	**EUR/GBP**	**EUR/JPY**	**EUR/USD**
Obs	1305	1305	1305	1305
Sum of Wgt.	1305	1305	1305	1305
Mean	1.139662	.8174315	130.9536	1.195248
Std. Dev.	.0679658	.0581779	8.123611	.1077133
Variance	.0046193	.0033847	65.99305	.0116022
Skewness	.1251284	-.4403776	-.4321573	.472008
Kurtosis	1.487401	2.075686	2.633615	1.748748

Source: Author's Computation 2022

We carried out a descriptive statistic of our data in order to understand the basic features and behavior of the data used in the study. They provide simple summaries about the sample and the measures. Together with this we presented a simple graphics analysis, that form the basis of virtually every quantitative analysis of data in the sequent section.The summary statistics of the variables pre-pandemic show that the means, standard deviation, variance, skewness and kurtosis of the data. EUR/TRY, EUR/UAH, EUR/CNY and EUR/BRL have the mean 3.342786, 23.34391, 7.637897 and 3.523268 respectively. The standard deviation which is an indication of spread of the distribution away from mean is highest for Ukraine currency pairs (EUR/UAH) with the value of 7.458248. This reflects a higher degree of volatility for Ukraine hryvnia compared with other pairs. EUR/BRL has a standard deviation of .4418534 which is lowest among the emerging countries examined during the period under observation. EUR/TRY, EUR/UAH, EUR/CNY and EUR/BRL have a skewness of .8646271, -.4869149, .1097712 and 0.3233281 respectively. From this only EUR/UAH is the only variable which is negatively skewed, depicting that distribution dove-tailed to the left. While the kurtosis measuring the degree of peakedness revealed that all the distributions were all platykurtic meaning they fall below the normal distribution.

Similarly, currency pairs from emerging countries EUR/CHF, EUR/GBP, EUR/JPY and EUR/USD have the mean value of 1.139662, 0.8174315, 130.9536 and 1.195248 respectively. The standard deviation which is an indication of spread of the distribution away from mean is highest for Japanese yen currency pairs (EUR/JPY) with the value of 8.123611. This reflects a higher degree of volatility for Japanese Yen compared with other pairs. EUR/USD has a standard deviation of .1077133 which is lowest among the emerged countries examined during the period under observation. This also points attention to the great level of stability in US foreign exchange. EUR/CHF, EUR/GBP, EUR/JPY and EUR/USD have a skewness of .1251284, -.4403776, -.4321573 and 0.472008 respectively. From this only EUR/GBP and EUR/JPY are negatively skewed while the EUR/CHF and EUR/USD are positively skewed. Moreso like the pairs for the emerging countries, all the distributions were all platykurtic meaning they fall below the normal distribution.

Figure 1: a. Graphical Representation and data visualization for Emerging Countries

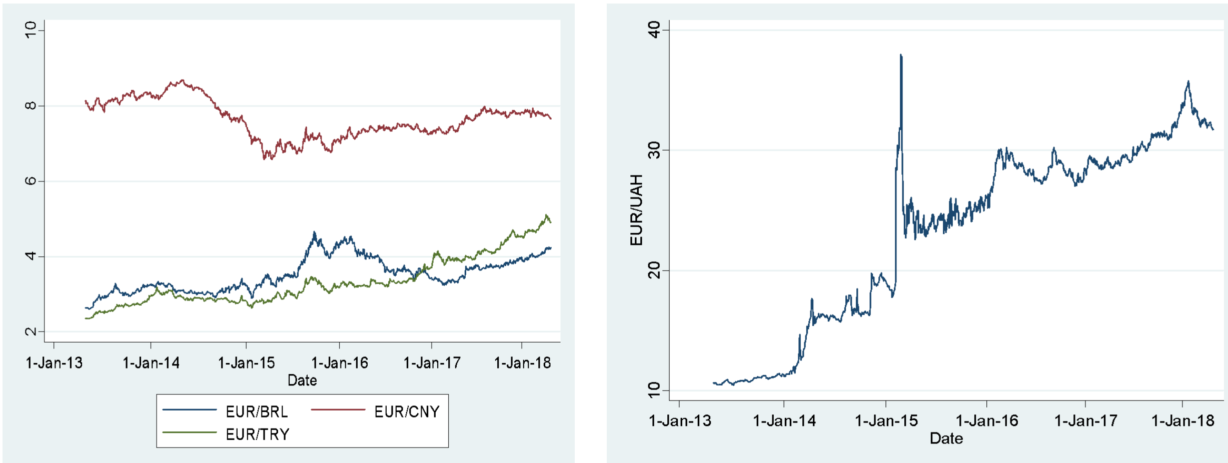
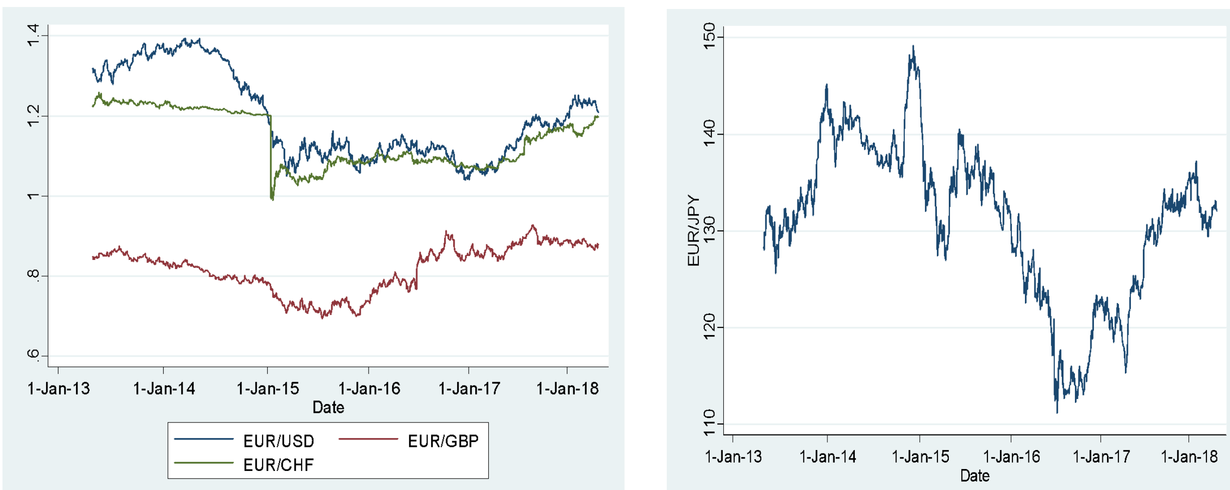


Figure 1: b. Graphical Representation and data visualization for Emerged Countries



Plotting the graph of the series for visualization is a major step toward our model estimation and determining the stationarity of our variables. One stylized fact of the GARCH model, which is comparable to the ARCH, is that it shows series volatility clustering. The mean reversion found in the graphical plots above is one evident truth with the EUR/BRL, EUR/TRY, and EUR/UAH currency pair pre-pandemic period. GARCH models were among the first to consider the phenomena of volatility clustering. The (squared) volatility in a GARCH(1,1) model is determined by the volatility of the previous period.

Unpredictability clustering means that big changes will almost always be followed by big changes of the opposite sign, or small changes will almost always be followed by little changes.

The GARCH plot, which was developed in the mid-1980s, played a key role in propagating this fact in econometric models. By relying on the past squared of innovations for conditional variance. It clearly captures the effect that once the market is highly volatile, it is more likely to stay that way than to calm down (De Vries, G.C., and Leuve, K.U., 1994). In this way, GARCH models not only predict the direction of the exchange rate's time-varying conditional variance, but also enable us to detect the appropriate contingent instability. The variance cluttering effect would show a stability of pre-pandemic currency pairs by observation in figure 1b, as evidenced by the above exchange rate depicted in the graph especially for EUR/CHF and EUR/USD from 2013 to 2015.

A significant deterioration in currency can be observed for EUR/UAH in figure 1a. with a major spike in January and February 2015. This can be traced to the currency meltdown experienced in Ukraine at this period in 2015. (Anders Åslund 2015)

However, currency pairs for wealthy countries, as well as currency pairs for emerging and developing countries during the pandemic, exhibit some volatility. As a result, before we estimate the ARCH and GARCH models, we must do a unit root test as shown below.

3.2.1 Unit Root

Unit root tests of the time series properties of the data are analyzed to determine the order of integration of the variables employed in the model, which are novel contemporary advancements in time series modeling. If the null hypothesis is accepted, a series is said to be stationary at level; otherwise, reject the stationarity test at level and move on to the first difference. The unit root test based on Augmented Dickey Fuller was performed.

Table 6. Unit Root test

	Prepandemic	
Variable	**T-Statistic**	**Order of Integration**
EUR/CHF	-0.679***	I(1)
EUR/GBP	-2.069**	I(1)
EUR/JPY	-1.019**	I(1)
EUR/USD	-1.095**	I(1)
EUR/BRL	-3.120***	I(1)
EUR/CNY	-2.011 **	I(1)
EUR/TRY	-2.011**	I(1)
EUR/UAH	-3.413 **	I(1)

Author's computation 2022

**** significant at 5% level of significance * significant at 1% level of significance**

The results as presented in Table 2 clearly reveals that prepandemic all the currency pairs namely EUR/CHF, EUR/GBP, EUR/JPY, EUR/USD, EUR/BRL, EUR/CNY, EUR/TRY and EUR/USD only became stationary after first differencing, that is I (1). Similarly all the currency pairs only become stationary at first differencing during the pandemic except for EUR/GBP and EUR/BRL which were stationary at level. Going forward, we proceed to conduct the estimate of the ARCH and GARCH models.

3.2.2 Model Estimation: ARCH and GARCH Estimation

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is used to calculate the parametric measure of exchange rate volatility. This is in contrast to several previous studies that used unconditional measures of volatility, such as variance or standard deviation, and failed to notice that there are fascinating patterns in volatility research, such as time-varying and clustering features. This supports the GARCH model selection shown in the table below. For this exchange rate analysis, table 4.2 shows the parameter of estimates and their accompanying p-values for developed and emerging economies in two different periods: pandemic and during pandemic, using the GARCH (1, 1) model (The original STATA table can be found in the Appendices).

Following Asteriou & Hall (2021) GARCH (1, 1) model can be extended to a GARCH (p,q) model where p - lagged terms of the conditional variance (h) and q - lagged terms of the squared error (u^2). That is:

$$\text{GARCH }((p,\ q)\text{: } h_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} \beta_1 u^2_{t-i}$$

$$\text{GARCH }(1,\ 1)\text{: } Price_t = \varphi + \sum_{k=1}^{1} \theta_1 Price_{t-1} + \sum_{i=1}^{1} \beta_1 u^2_{t-1}$$

Table 7: ARCH and GARCH Result for Emerging Countries

ARCH family regression	
Sample: 30-Apr-13 - 30-Apr-18, but with gaps	Number of obs = 5220
Distribution: Gaussian	Wald chi2(.) = .
Log likelihood = -11985.17	Prob > chi2 = .

Price	Coef.	OPG Std. Err.	z	P>z	[95% Conf.	Interval]
Price						
_cons	3.239892	.0021271	1523.18	0.000	3.235723	3.244061
ARCH						
arch						
L1.	1.000308	.0302394	33.08	0.000	.9410398	1.059576
garch						
L1.	-3.63e-06	2.32e-06	-1.56	0.118	-8.18e-06	9.19e-07
_cons	.0009379	.0001227	7.65	0.000	.0006975	.0011784

Source: Author's Computation 2022

From table 3, the coefficient of the constant variance term, the ARCH is positive for both emerging economies. The coefficients of the constant terms and GARCH were negative for emerging economies pre-pandemic time. The time varying volatility includes a constant and a component which depends on past errors. As a proof that this model satisfies the stability condition, the summation of the coefficient of GARCH term and the constant term is less than one for emerging. The statistically significant negative coefficient of the GARCH pre-pandemic is not surprising. For the variance equation, pre-pandemic period, the coefficient of the ARCH effect is positive for emerging economies. The coefficient of the ARCH was positive and significant at less than 5% level of significant level. This depicts the presence of high volatility clustering of exchange rate before the outbreak of pandemic in emerging economies. However, from the estimate the ARCH coefficient is 1.000308 depicting volatility clustering character of exchange rate for emerging economies.

On the GARCH coefficients, before the pandemic, $\beta\ represented\ by\ L1\ in\ the\ table$ for emerging economies was -0.00000363 (-3.63e-06) but not statistically significant at less than 5% level of significance. This depicts a less exchange rate volatility pre-pandemic period for the emerging economies. It can therefore be inferred that exchange rate volatility consequent to the outbreak of the coronal virus pandemic was significantly higher in emerging economies compared with pre-pandemic period as evidenced in the estimated outcome. These findings corroborate with Feng et al., (2021) study on what is the exchange rate volatility response to COVID-19 using 20 sampled economies evidenced that the increase in the percentage of biweekly confirmed cases has indeed boosted exchange rate volatility at a 5% significance level.

Table 8: ARCH and GARCH Outcome for emerged economies before the pandemic

GARCH family regression	
Sample: 30-Apr-13 - 30-Apr-18, but with gaps	Number of obs = 5220
Distribution: Gaussian	Wald chi2(.) = .
Log likelihood = -9146.426	Prob > chi2 = .

	Price	Coef.	OPG Std. Err.	z	P>z	[95% Conf.	Interval]
Price							
	_cons	1.089422	.0003054	3567.76	0.000	1.088824	1.09002
ARCH							
	arch						
	L1.	.9979231	.0340936	29.27	0.000	.9311009	1.064745
	garch						
	L1.	1.09e-09	9.96e-10	1.09	0.274	-8.63e-10	3.04e-09
	_cons	.0000216	1.85e-06	11.68	0.000	.000018	.0000252

Source: Author's Computation 2022

The coefficient of the constant variance term, the ARCH is positive for both emerged economies. The coefficients of the constant terms and GARCH were positive for emerged economies pre-pandemic time. The time varying volatility includes a constant and a component which depends on past errors. This model was stationary since the addition of $\theta\ and\ \beta$ is less than 1. The coefficient of the constant variance term, the ARCH is positive for emerged economies. The coefficients of the constant terms and GARCH was also positive for emerged economies pre-pandemic time. The time varying volatility includes a constant and a component which depends on past errors. The statistically significant positive coefficient of the GARCH pre-pandemic is not a strange as this depict that there was a high volatility during the period under examination for the selected emerged economies. For the variance equation, pre-pandemic period, the coefficient of the ARCH effect is positive for the economies. The coefficient of the ARCH was positive and significant at less than 5% level of significant level. This depicts the presence of high volatility clustering of exchange rate prior to the outbreak of pandemic in emerged economies. Evidence of such volatility clustering is traceable to EUR/USD and EUR/CHF from the visualization under the period under consideration

However, from the estimate the ARCH coefficient is 0.9999 depicting volatility clustering character of exchange rate for emerged economies. On the GARCH coefficients, before the pandemic, $\beta\ captured\ as\ L1$ for emerging economies was 1.09e-09 not statistically significant at less than 5% level of significance. This depicts a less exchange rate volatility pre-pandemic period for the emerged economies. It can therefore be inferred that exchange rate volatility prior to the outbreak of the coronal virus pandemic was higher in emerging economies compared with pre-pandemic period as evidenced in the estimated outcome.

Conclusion

Of late, with the inception of the novel corona pandemic, a plethora of economic literature has emerged on volatility in financial markets based on modeling and forecasting. A number of these studies have centered on the equity and security market with less attention on the exchange rate of economies. In the highest case those who have undertaken to explore this aspect have done so on a limited currency pair. This is unfortunate given the importance of exchange rates to our economies. Moreover, forecasts of exchange rate volatility are important inputs into financial market risk assessment calculations like value at risk, macro econometric models and option pricing formulas for futures contracts.

This paper is the first attempt to investigate the impact of COVID-19 on the exchange rate market based on comparison effects on emerging economies and emerged economies. The results suggest that changes in the number of cases and deaths and consequent of lockdowns have a positive impact on emerging market currency exchanges rate with less strong on emerged economies currency pairs in this study.

With the new data covering the period from 2013 to 2018, the coefficients of the constant variance term, the ARCH, are positive and significant for both emerged and emerging economies before the pandemic. This outcome is likewise significant and positive for previous pre-pandemic and pandemic outcomes obtained for both emerged and emerging economies. The global outcome depicts the presence of high volatility clustering of exchange rate before the outbreak of pandemic in both emerged and emerging economies. However, from the new data the ARCH coefficient of 1.000308 is for emerging economies is higher than ARCH coefficient value of 0.9979231 in emerged economies which is similar with the ARCH coefficient of 1.015027 for emerging ARCH coefficient value of 0.9961575 in emerged economies in previous result using. Compared with the outcome during the pandemic, the ARCH coefficient still possessed the positive sign but was not significant. Hence, it can be deduced that the pandemic had a significant effect on the volatility clustering character of exchange rate for both emerging and emerged economies.

From previous result during the pandemic, the GARCH coefficients, β which stands for L1 under GARCH for emerging economies was 0.995 and statistically significant at less than 5% level of significance. This depicts a very high exchange rate volatility traceable to the effect of the pandemic for emerging economies while during the same period for the emerged or developed economies β was 4.44E-10 and statistically significant at less than 5% level of significance. This indicates a very low volatility in exchange rate for emerged economies. It can therefore be inferred that exchange rate volatility consequent to the outbreak of the coronal virus pandemic was significantly higher in emerging economies compared with emerging economies. This stands in contrast to the present outcome which revealed low volatility (L1) for emerging economies. However, the outcome obtained shares similar low volatility evidence before the pandemic for both emerging and emerged economies.

Finally, Esquivel & Larraín (2002) study on the Impact of G-3 Exchange Rate Volatility on Developing Countries revealed that developed countries exchange rate volatility negatively developing countries exchange rate stability thus producing greater volatility.

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Appendices

Appendix 1: Pre-Pandemic Descriptive Statistics

EUR/CHF

	Percentiles	Smallest		
1%	1.06277	1.06103		
5%	1.0734	1.06117		
10%	1.08564	1.06135	Obs	522
25%	1.0992	1.06143	Sum of Wgt.	522
50%	1.12923		Mean	1.126182
		Largest	Std. Dev.	.0318678
75%	1.14318	1.19771		
90%	1.16947	1.19775	Variance	.0010156
95%	1.1822	1.19892	Skewness	.1027926
99%	1.19756	1.19926	Kurtosis	2.524287

EURGBP

	Percentiles	Smallest		
1%	.83322	.82979		
5%	.84473	.83032		
10%	.8526	.83055	Obs	522
25%	.86351	.83105	Sum of Wgt.	522
50%	.879665		Mean	.8779192
		Largest	Std. Dev.	.0191713
75%	.89163	.92478		
90%	.89956	.92641	Variance	.0003675
95%	.9059	.92839	Skewness	-.1487793
99%	.92278	.93212	Kurtosis	2.642494

EURJPY

	Percentiles	Smallest		
1%	117.231	116.161		
5%	118.086	116.433		
10%	119.481	116.662	Obs	522
25%	121.112	116.847	Sum of Wgt.	522
50%	125.1185		Mean	125.1075
		Largest	Std. Dev.	4.432724
75%	129.073	132.892		
90%	130.957	132.893	Variance	19.64905
95%	131.703	133.11	Skewness	-.0275494
99%	132.626	133.116	Kurtosis	1.752093

EURUSD

	Percentiles	Smallest		
1%	1.084058	1.078772		
5%	1.098587	1.079471		
10%	1.102633	1.080964	Obs	522
25%	1.113834	1.083705	Sum of Wgt.	522
50%	1.132451		Mean	1.140325
		Largest	Std. Dev.	.0365053
75%	1.15934	1.240803		
90%	1.186676	1.241619	Variance	.0013326
95%	1.230769	1.241928	Skewness	1.124031
99%	1.238467	1.245501	Kurtosis	3.846027

EUR/CNY

	Percentiles	Smallest		
1%	7.4751	7.4059		
5%	7.5256	7.4062		
10%	7.5584	7.4382	Obs	522
25%	7.6545	7.4477	Sum of Wgt.	522
50%	7.76765		Mean	7.754777
		Largest	Std. Dev.	.1356935
75%	7.8488	8.0571		
90%	7.9267	8.0631	Variance	.0184127
95%	7.9648	8.0748	Skewness	-.196794
99%	8.0213	8.0832	Kurtosis	2.402844

EUR/BRL

	Percentiles	Smallest		
1%	4.0222	3.9838		
5%	4.1391	3.9888		
10%	4.2099	4.0005	Obs	522
25%	4.2798	4.0063	Sum of Wgt.	522
50%	4.40295		Mean	4.418854
		Largest	Std. Dev.	.1851406
75%	4.5377	4.857		
90%	4.6681	4.9192	Variance	.034277
95%	4.7468	4.9318	Skewness	.2416199
99%	4.8425	4.9338	Kurtosis	2.792989

EUR/TRY

	Percentiles	Smallest		
1%	4.7076	4.6685		
5%	4.9344	4.6894		
10%	5.2076	4.6903	Obs	522
25%	5.976	4.6981	Sum of Wgt.	522
50%	6.30625		Mean	6.182701
		Largest	Std. Dev.	.6168013
75%	6.5498	7.7114		
90%	6.7958	7.7264	Variance	.3804439
95%	7.0961	7.7631	Skewness	-.4691755
99%	7.6504	7.8533	Kurtosis	3.280149

EUR/UAH

	Percentiles	Smallest		
1%	25.9158	25.7468		
5%	26.4241	25.7514		
10%	26.6916	25.775	Obs	522
25%	27.8388	25.8034	Sum of Wgt.	522
50%	30.5081		Mean	29.88706
		Largest	Std. Dev.	2.097939
75%	31.6684	33.01		
90%	32.3173	33.0175	Variance	4.401348
95%	32.6459	33.0331	Skewness	-.4075932
99%	33.0005	33.0453	Kurtosis	1.838058

Appendix 2: During Pandemic Descriptive Statistics

EUR/BRL

	Percentiles	Smallest		
1%	5.2363	4.9805		
5%	5.6379	5.043		
10%	5.8129	5.1046	Obs	520
25%	6.0878	5.1777	Sum of Wgt.	520
50%	6.30295		Mean	6.253258
		Largest	Std. Dev.	.3250633
75%	6.4744	6.8296		
90%	6.6314	6.8618	Variance	.1056662
95%	6.69955	6.9038	Skewness	-.8502126
99%	6.7983	6.9584	Kurtosis	4.0028

EUR/CHY

	Percentiles	Smallest		
1%	7.1398	7.082		
5%	7.1882	7.0875		
10%	7.2136	7.0917	Obs	520
25%	7.60775	7.1025	Sum of Wgt.	520
50%	7.77265		Mean	7.714206
		Largest	Std. Dev.	.2743284
75%	7.90235	8.2547		
90%	8.0051	8.2555	Variance	.0752561
95%	8.14625	8.2573	Skewness	-.5510237
99%	8.2277	8.3017	Kurtosis	2.734128

EUR/TRY

	Percentiles	Smallest		
1%	6.9234	6.7635		
5%	7.3181	6.8178		
10%	7.55265	6.8574	Obs	520
25%	8.5996	6.8699	Sum of Wgt.	520
50%	9.47935		Mean	9.941617
		Largest	Std. Dev.	2.337224
75%	10.29255	16.1939		
90%	15.05615	16.6877	Variance	5.462618
95%	15.44625	17.748	Skewness	1.366968
99%	15.6951	18.4455	Kurtosis	4.269001

EUR/UAH

	Percentiles	Smallest		
1%	28.5975	27.6235		
5%	29.256	27.6742		
10%	29.79955	27.7579	Obs	520
25%	30.5867	27.9107	Sum of Wgt.	520
50%	32.2546		Mean	31.9637
		Largest	Std. Dev.	1.593096
75%	33.31235	34.7949		
90%	33.8165	34.8097	Variance	2.537956
95%	34.1409	34.8198	Skewness	-.3597422
99%	34.6544	34.9452	Kurtosis	2.14672

EURCHF

	Percentiles	Smallest		
1%	1.03592	1.03373		
5%	1.040145	1.03473		
10%	1.04515	1.03479	Obs	520
25%	1.059235	1.03511	Sum of Wgt.	520
50%	1.076215		Mean	1.073676
		Largest	Std. Dev.	.0184178
75%	1.083775	1.1091		
90%	1.0978	1.1092	Variance	.0003392
95%	1.104505	1.11063	Skewness	-.2097757
99%	1.1088	1.11211	Kurtosis	2.414356

EURUSD

	Percentiles	Smallest		
1%	1.080124	1.065848		
5%	1.087146	1.068753		
10%	1.106533	1.076473	Obs	520
25%	1.132355	1.077633	Sum of Wgt.	520
50%	1.176471		Mean	1.16524
		Largest	Std. Dev.	.0395083
75%	1.192599	1.226873		
90%	1.214542	1.229861	Variance	.0015609
95%	1.218873	1.229906	Skewness	-.4970847
99%	1.225325	1.233776	Kurtosis	2.336231

EURJPY

	Percentiles	Smallest		
1%	115.847	114.697		
5%	117.4175	115.285		
10%	118.8965	115.369	Obs	520
25%	123.7905	115.63	Sum of Wgt.	520
50%	127.942		Mean	126.6052
		Largest	Std. Dev.	4.68354
75%	130.1515	133.807		
90%	131.9575	133.89	Variance	21.93555
95%	132.761	133.929	Skewness	-.6652417
99%	133.76	133.983	Kurtosis	2.501219

EURGBP

	Percentiles	Smallest		
1%	.83293	.8318		
5%	.83651	.83183		
10%	.842915	.832	Obs	520
25%	.85421	.83229	Sum of Wgt.	520
50%	.86828		Mean	.874009
		Largest	Std. Dev.	.0247976
75%	.898425	.9245		
90%	.906945	.92694	Variance	.0006149
95%	.91092	.92799	Skewness	.205956
99%	.92309	.9423	Kurtosis	1.813113

Appendix 3: ARCH and GARCH Outputs

Appendix 3.1: Emerging Economies Pre-Pandemic

ARCH family regression		
Sample: 1-Mar-18 - 28-Feb-20, but with gaps	Number of obs =	2,088
Distribution: Gaussian	Wald chi2(.) =	.
Log likelihood = -4954.167	Prob > chi2 =	.
OPG		
Pricce Coef. Std. Err. z	P>z [95% Conf.	Interval]
Pricce		
_cons 7.722897 .0025471 3032.03	0.000 7.717905	7.72789
ARCH		
arch		
L1. 1.015027 .0501912 20.22	0.000 .9166545	1.1134
garch		
L1. -3.52e-06 2.18e-06 -1.61	0.108 -7.80e-06	7.67e-07
_cons .0008324 .0002082 4.00	0.000 .0004243	.0012406
.		

Appendix 3.2: Emerged Economies Pre-Pandemic

ARCH family regression		
Sample: 3/1/2018 - 2/28/2020, but with gaps	Number of obs =	2,088
Distribution: Gaussian	Wald chi2(.) =	.
Log likelihood = -2791.862	Prob > chi2 =	.
OPG		
Price Coef. Std. Err. z	P>z [95% Conf.	Interval]
Price		
_cons 1.128981 .0003108 3632.68	0.000 1.128372	1.12959
ARCH		
arch		
L1. .9961575 .0536171 18.58	0.000 .8910698	1.101245
garch		
L1. -3.59e-10 1.65e-09 -0.22	0.828 -3.58e-09	2.87e-09
_cons .0000107 2.15e-06 4.99	0.000 6.51e-06	.0000149

Appendix 3.3: Emerging Economies During Pandemic

ARCH family regression		
Sample: 2-Mar-20 - 25-Feb-22, but with gaps	Number of obs =	2080
Distribution: Gaussian	Wald chi2(.) =	.
Log likelihood = -4815.349	Prob > chi2 =	.
OPG		
Price Coef. Std. Err. z	P>z [95% Conf.	Interval]
Price		
_cons 7.766993 .0039943 1944.51	0.000 7.759164	7.774821
ARCH		
arch		
L1. .9990746 .0557752 17.91	0.000 .8897573	1.108392
garch		
L1. -3.51e-08 5.37e-06 -0.01	0.995 -.0000106	.0000105
_cons .0012795 .0002771 4.62	0.000 .0007365	.0018225

Appendix 3.4: Emerged Economies During Pandemic

ARCH family regression		
Sample: 3/2/2020 - 2/25/2022, but with gaps	Number of obs =	2080
Distribution: Gaussian	Wald chi2(.) =	.
Log likelihood = -3032.174	Prob > chi2 =	.
OPG		
EURCHF Coef. Std. Err. z	P>z [95% Conf.	Interval]
EURCHF		
_cons 1.08058 .0002927 3691.33	0.000 1.080006	1.081154
ARCH		
arch		
L1. .9970402 .0535703 18.61	0.000 .8920444	1.102036
garch		
L1. 4.44e-10 6.23e-10 0.71	0.476 -7.77e-10	1.66e-09
_cons 7.46e-06 1.31e-06 5.68	0.000 4.89e-06	.00001
.		

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