THE IMPACT OF EXCHANGE RATES VOLATILITY ON EXPORTS: THE CASE OF BREXIT

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ABSTRACT

Purpose – The term Brexit, the United Kingdom's withdrawal from the European Union, is linked with the uncertainty raised due to the ambiguity of the economic relationship to be adopted between the U.K and the EU. This uncertainty is translated directly into a significant fluctuation of the British pound. Therefore, this research highlights the impact of the Brexit referendum on the British pound against the Euro, test the relationship between exchange rate volatility and U.K's exports to Eurozone countries (Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherland, Portugal, Slovakia, Slovenia, and Spain), and finally, detect the presence of a structural break in the relationship between exchange rate volatility and exports post-Brexit referendum.

Design/ methodology/ approach - This research employs monthly data spanning from January 1st, 2010 to August 31st, 2020 when calculating the GBP/EUR exchange rate volatility using the EWMA, GARCH (1, 1), and the EGARCH (1, 1) models. The three-error statistics (RMSA, MAE, and MAPE) are utilized to determine the best-fitted model for GBP/EUR exchange rates. Subsequently, the Auto-Regressive Distributed Lag (ARDL) bound testing approach is applied to analyze the level relationships between exchange rate volatility on U.K's exports to Eurozone countries using monthly data spanning from January 2010 to August 2020. Our regression model takes into consideration the Commodity Term of Trade (TOT), the weighted average Industrial Production Index (IPI), and the Real Effective Exchange Rate (REER). Finally, the Chow test is performed to detect the presence of a structural break in the export regression due to the Brexit referendum (June 2016).

Findings – In regards to the results of this research, it demonstrated that, first, no model appeared to outperform another when modeling the GBP/EUR exchange rate volatility compared to the realized volatility. Thus, the GARCH (1, 1) was chosen to proceed with since it was the aftermost to the realized volatility as seen graphically. Towards the purpose of our second research question, it is shown that exchange rate volatility has a negative impact on exports for both the short and long run, while the Real Effective Exchange Rate has a negative impact on exports for the short-run only. The remaining dependent variables, TOT and IPI, have been shown to exert a statistically significant and positive impact on U.K's exports to Eurozone countries for both the short-run and long-run. Finally, performing the Chow test did not show any significant structural break on time of the referendum, however, by 2018 a structural break appeared concurrently with the ongoing negotiations to specify an exit deal.

Research limitations/implications – The limitation faced is the lack of available data that would have given a more robust outcome to our analysis.

Practical implications – This research helps individuals or firms to understand the link between volatile exchange rates and exports.

Originality/value – This research reinforces the hypothesis of a negative relationship between exchange rate volatility and exports. On the other hand, it highlights the influence of the Brexit referendum on the U.K's exports to its major trading partners, the Eurozone.

Keywords – Brexit, TOT, IPI, REER, Exchange rate volatility, Exports, United Kingdom, Eurozone, GARCH (1, 1), EGARCH (1, 1), EWMA, Realized volatility, ARDL, and Chow test.

CHAPTER 1:

INTRODUCTION:

1.1.1 General Background about the Topic

Over the last few decades, monitoring volatility has drawn the attention of academics and practitioners since volatility can be attributed to the economic fundamentals in the decision-making process, risk management, derivatives pricing, and hedging (Miah et al.,2016). Volatility is a crucial indicator to evaluate the size and the persistence of any shock incurred in the financial market. From this perspective, this study highlights a very particular case; the Brexit vote. The referendum vote has induced shock waves and uncertainty that caused the global stock and exchange rate market to be increasingly volatile. The uncertainty rose due to the ambiguity about the future relationship between the U.K and the EU, especially that the U.K is one of the largest trade partners for the EU.

The European Union concept started since the 1950s, where the European Coal and Steel Committee (ECSC) began to unite European countries politically and economically in order to prevail peace and end bloody wars between neighbours. The ECSC started with six founding members: France, Germany, Italy, Belgium, Luxembourg and Netherlands, whereas this union established a common market that allowed the free movement of goods, services, people and money, set standards policies and eliminated the customs duties between its members. The reduction of trade barriers and the elimination of tariff costs have allowed the enhancement of market opportunities due to the free movements (Bitzenis et al., 2006). In other words, the free movement enables firms to expand and open new branches at any member state and allows qualified and skilled workers to seek and access job opportunities anywhere within Europe. Such movements trigger economic growth (Katainen, 2017). Furthermore, due to the liberalization of the internal market, it offers a wide range of goods and services and as a result, it ends the monopoly and increases competition which also contributes in boosting the growth of the economy. The EU imposes a standardized law for all member-state in order to ensure and protect the right of consumers and guarantee a high standard of safety, health, and environment across Europe.

Another important achievement of the European Monetary Union (EMU) is the unification of currency where they've adopted the Euro. This unification ensured stability while reducing uncertainty about future exchange rate fluctuation, hence, transaction cost is therefore reduced. The elimination of exchange rate risk had not only reduced investment risks but also boosted the stimulation of foreign investment. Moreover, EMU ensured homogeneity in the EU due to the transparency of prices which led to further reduction in the level of prices, and as a result, it stimulates trade between member states, and promotes economic efficiency within the euro zone (Stankovic, 2013).

Nowadays, the European Union consists of 28 member countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the United Kingdom.

This union is governed by three initial bodies:

The EU council: its main role is to set policies and suggests new enactments.

The European Parliament: it debates and approves the new legislation and policies proposed by the Council.

The European Commission Staff: it executes the approved laws and policies (Amadeo, 2018).

1.1.2 EU and UK's Relationship

The EU and United Kingdom have a rocky relationship since the 1960s, when the French President Charles de Gaulle has rejected the membership of Britain. However; by 1973, Britain joined the European Union but soon enough in 1975, EU & U.K held a referendum to exit this union. At that time, 67% of the people opted to stay in the EEC (European Economic Community). On the other hand, many citizens complained and resisted the integration claiming that European Parliament and the European Court of Justice have been diluting British sovereignty. Britain had an important political, economical, and military magnitude. Therefore, the Continental Europe was very interested in keeping Britain in the bloc and allowed them to bypass fiscal rules, the Schengen border, and reduced their contribution to the common budget. Moreover, they eased for British labor the free movement, and allowed London to be the center of financial Euro zone (Wang, et al, 2018). However, there was a controversy between the two parties, the EU wanted to pursue a closer integration to strengthen the union while U.K was only interest in the free movement of goods and services. Thus, by 2016 with the ongoing migration crisis and the troubled euro zone, the U.K Anti-Europe sentiment has been triggered, and that's when Cameron announced in February of that year a referendum on Britain membership of EU. By June 23rd, 2016 the United Kingdom voted in a referendum to end its membership in the European Union. This event caused turmoil in the financial markets leading to instant losses especially for financial institutions (Fernandes, 2016).

1.1.3 Brexit

On June 23rd of 2016, Britons astonished the world by voting to leave the European Union with a 51.9% against 48.1% opting to stay. Leaving Europe would affect U.K's economic activity negatively either for the short –term due to uncertainty or for the long-term via trade (Armstrong et al., 2016). United Kingdom is considered the world's second-largest export of services and one of the most important trade partners of the EU. As a result of the exit, the U.K loses its trade privileges with the EU. The U.K has officially started the Brexit process since the 27th of March 2017, by which it has up to a period of 2 years in order to negotiate a treaty that cease to apply. Any agreement reached should surpass European Council qualified majority and the approval of the European Parliament. Mainly, the U.K has several trade regimes that have to choose from;

1-European Free Trade Association (EFTA) "Soft Brexit": U.K can rejoin the EFTA and choose to be a member in European Economic Area (EEA), similarly to the case of Norway. Thereby, U.K will be allowed to participate in E.U single market, and access external free trades arranged by E.U and enjoy tariff free on their traded goods. However, in return U.K has to allow the free mobility of people, contribute to E.U budget, and abide to the single market's regulations (Chang, 2017). Moreover, U.K's institution would still be able to offer service through EEA while they retain their "passporting" rights. The downside of being a member of EEA is that U.K has to set its own external tariff, administrate their own negotiation with non-EU countries, and satisfy the rule of origin on their export so that they can enter to the E.U tariff free (Dhingra, et al, 2017). Or instead, it could attain a status similar to Switzerland, by which U.K can still enter bilateral agreements with the E.U and gain from a decrease in fiscal transfers to E.U, but on the other hand, U.K has to allow the mobility of labour forces (Chang, 2017). In all cases, being a member of EEA would mean that U.K have to adhere to E.U's economic regulations without having the right to decide or have a say about them ("pay with no say") (Dhingra, et al, 2017).

However, since migration was one of the reasons U.K decided to leave E.U, then EFTA option seems to be irrelevant. Dhingra, et al (2017) proclaims that "the U.K government has announced its plans to leave the single market following Brexit".

2- U.K as a member in E.U Custom Union: following this option, U.K has the ability to set its own migration policy and ensure no added tariff on U.K's traded goods. However, it will no longer have the authority to set its own trade agreements with other countries and authorized access for service trade in the market is not guaranteed, similarly to the status of Turkey (Chang, 2017). Dhingra, et al (2017) also proclaims that Britain eliminated such an option.

3- Adoption of WTO rules (World Trade Organization) "Hard Brexit": The geographic proximity and U.K access to the single market have helped in creating close and vital trade flow between E.U's members. If Britain were unable to set a Free Trade Agreement (FTA) or any other kind of agreements with the E.U, then U.K's trades with E.U and the rest of the world would be governed by the WTO's rules. These rules implicate the followings:

Each member should imply common tariffs to all other WTO members and allow Most Favored Nation (MFN) market access. Based on this principle, countries can join FTAs (i.e. EU customs union, North America Free Trade Agreements (NAFTA), and etc…) while granting developing countries the privilege to access the market.

Exports between other WTO members and E.U will be subjected to MFN importing tariffs, and as a result, it will increase the cost of trade between countries. WTO provides no article regarding the free movement of people. Therefore, U.K's concern about labour mobility is terminated (Dhingra et al., 2017).

Chang (2017) states that under any of the above-mentioned scenarios, Britain would suffer from a 2-year recession right after the actual exit on March 2019. Moreover, all these scenarios are exposed to high uncertainty such as social-economic uncertainty; trends regarding world economic integration, military landscape, etc, therefore, scenario analysis might be irrelevant or unsuitable.

1.1.4 Problem Definition

Since the Brexit vote in 2016, continuous negotiations have been taking place between the U.K and the EU in order to set out the divorce deal, also known as the withdrawal agreement. The actual exit of U.K, as previously mentioned, was due by the 29th of March, 2019. During the 2-year period, The MPs voted three times consecutively against the withdrawal deal reached for by their prime minister, Theresa May, therefore, a new deadline has been scheduled; it's by the end of October 2019. The resignation decision of Theresa May by the 24th of May has added further turmoil to Britain's exit plan and induced more uncertainty in the market causing the GBP/EUR to be more volatile.

Bloomberg has developed a Barometer which is a customized index to reflect how the British economy is responding to the Brexit process. The barometer takes into consideration inflation, employment, uncertainty, and growth. After the resignation of Theresa May, the barometer has shown a negative indicator (-8.8) which represent a deterioration in the British economy as a response to Brexit news.

1.2 Need for the Study

The British Exit from the EU has raised many questions regarding whether this exit will contribute to an increase or decrease in economic growth or its real income along with many other aspects.

Hence, there is a whole series of study that examined the impact of Brexit on different prospects such as trade flow, exchange rates, immigrations, etc. In addition, modeling the volatility has also drawn the attention especially that of exchange rates since an increase in exchange rates volatility (risk) increases the transaction cost, thus, reduces the gains from international trades. Many studies have examined the relationship between exchange rate volatility and the trade flow, however till our days neither consensus nor conclusive evidence are yet available.

To the best of our knowledge, no recent researches have yet examined the exchange rate volatility implication on U.K's exports to the Eurozone Countries (i.e. Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherland, Portugal, Slovakia, Slovenia, and Spain) due to the Brexit referendum.

1.3 Purpose of the Study

The lack of clarity about U.K's agreement with the EU has raised many concerns following the Brexit Referendum. This vagueness has led to a disturbance in the financial market immediately. Therefore, this research aims to shed light on 4 main points; first, the impact of Brexit on GBP/EUR exchange rates while revealing the facts of the volatility using three of the mostly used models; EWMA, GARCH (1, 1), and EGARCH (1, 1). Second, to detect whether the Brexit referendum has caused a structural break in the volatility of GBP/EUR exchange rates. Third, to investigate the impact of GBP/EUR exchange rate volatility on U.K's exports to Eurozone zone countries while applying the Autoregressive Distributed Lag (ARDL) approach. Finally, the Chow test will be performed to detect the presence of a structural break in the relationship between GBP/EUR exchange rates and the UK's exports to the Euro zone countries post-Brexit referendum.

Hence, the ultimate purpose of this study is to examine whether Brexit has an impact on U.K's exports due to a volatile GBP/EUR exchange rate.

1.4 Brief Overview of All Chapters

The structure of this study will be as follows. Chapter 2 tackles the existing literature related to exchange rates volatility modeling using various GARCH models. It will also tackle various studies performed to understand the link between exchange rates movements and exports of a country.

Chapter 3 outlines the methodology we will be adopting. Research questions are set and descriptive statistics of the GBP/EUR exchange rates returns over the selected time period, spanning between the 1st of January 2010 and the 31st of August 2020, are presented. The selected models, EWMA, GARCH (1, 1), and EGARCH (1, 1), are then described, while taking into consideration their features and characteristics, along with the adopted equations to model the volatility. Furthermore, the methodology used to reveal if there are changes in the volatility structure post-Brexit referendum is also presented. To test the relationship between the variability of exchange rates and U.K's exports to Eurozone countries, due to Brexit referendum for the time period spanning between January, 2010 and August, 2020, we employ the Autoregressive Distributed Lag (ARDL) approach. The ARDL approach will also be explained in details in term of its use and characteristics. Finally, the Chow test, will also be presented and explained in details.

Chapter 4 depicts the findings. The EWMA, GARCH (1, 1), and EGARCH (1, 1) model's parameters are estimated by maximizing the log likelihood function. Results obtained by calculating the three-error metrics to estimate the optimal model is illustrated and explained. Outputs acquired to regarding the testing of volatility structure changes of GBP/EUR post-Brexit is illustrated, as well. Moreover, the ARDL outputs aiming at testing the relationship between GBP/EUR exchange rate volatility and U.K's exports to Eurozone countries are presented and explained in details. Also, the finding obtained while running the Chow test is also presented.

Chapter 5 presents the analysis of the obtained results in chapter 4. The acquired results of this study are then compared to the results reached by previous researches and summarized in the literature review chapter. Practical and theoretical implications are then discussed. Recommendations for further potential researches are stated.

CHAPTER 2

REVIEW OF LITERATURE:

2.1 State of Knowledge and Previous Research

The referendum held by the British to leave the EU has stimulated a shock wave of uncertainty in the financial market immediately, causing the value of the pound to drop to its lowest value in history. Numerous studies have been investigating a range of possible outcome of Brexit on the U.K's economy, either for the short-term via uncertainty or long-term via trade. Therefore, this chapter will clarify two main points; the first point consists of understanding the stylized facts of exchange rate volatility in order to follow the behavior of GBP/EUR exchange rate and explain whether Brexit has an impact or not while using GARCH based models. The second point highlights previous studies detecting the correlation between exchange rates volatility and export. This is considerably vital especially that U.K has not only been benefiting from the free movements of good and service between EU countries, but also from more than 38 trade agreements that EU has set between non-European countries (Velthuijsen et al., 2016).

Volatility is referred to as a risk measurement based on the standard deviation of an asset's return for a given period, which shows the range in which the asset's price may increase or decrease. High volatility indicates a significant change in the asset's price over a short period, while low volatility indicates steadiness in the asset's price over a defined period (Song. et al, 2016). In terms of exchange rate volatility, particularly after the collapse of Bretton-Woods international monetary system in the 1970s, a new era for the global economy was enlightened, where researchers and policymakers were constantly concerned due to its significance on many aspects in a country's economy (Epaphra, 2017). Exchange rates volatility in this sense refers to the uncertainty emerging from unanticipated movements in exchange rates. In time of shocks, exchange rate fluctuation tends to have real economic costs on price stability, a country's financial stability, and firm profitability.

In the context of Brexit, Exchange rate is considered as the main cause for concerns, especially for the contemporary U.K economy. The referendum is one of the factors affecting exchange rates due to uncertainty associated with the ambiguity of the future relationship between the U.K and the EU. This circumstance is reasonably overwhelmingly influential for a well-defined period. Market expectations, different narratives, analysis and asymmetric information are major dynamics for the exchange rate, and considerably more vital when accounting for exchange rate movements (Nasir Et al, 2018).

Financial time series, such as exchange rates, stock returns, and other financial series exhibits stylized patterns, which are crucial for the specification of the right model. The most common stylized facts are mainly, volatility clustering and persistence. Volatility clustering implies the persistence of changes in the price of an asset. In other words, a large change is followed by a large change, and small changes tend to be followed by a small change. This feature signifies that news accumulates or clusters over time. Moreover, financial time series exhibits leverage effect as well, that is, a downward movement in the price of an asset is always followed by higher volatility than an upward movement of the same magnitude. Hence, price movements are negatively correlated with volatility (Epaphra, 2017). Furthermore, financial time series also exhibits leptokurtosis, meaning that the distribution of returns has a fatter tail and a higher peak at the mean when compared to a normal distribution. Finally, the volatility of high frequency data, such those of exchange rate, are persistent (Abdalla, 2012). Volatility persistence can be defined as the time taken for the volatility to move halfway back towards its unconditional mean following a deviation from it. The momentum in conditional variance is referred to as the persistence in conditional variance; past volatility elucidates current volatility (Charles et al., 2012).

The analysis of financial data has drawn the attention of academics and practitioners, especially over the past two decades. Several models have been suggested for capturing special features of financial data. Namely, Autoregressive Conditional Heteroskedasticity model (ARCH) and ARCH-type family introduced by Engle (1982) to highlight the problem of heteroskedasticity, volatility clustering, and leptokurtic properties and allowed volatility in the financial markets to be quantified. Heteroskedasticity, statistically speaking, occurs when the standard of errors of a defined variable is non-constant when monitored over a specified period of time. Bollerslev (1986) developed a General ARCH (GARCH) model that emphasizes on volatility persistence and characterized the conditional variance by its own lagged values and squared lagged values of shocks. By 1987 Engle et al. extended the ARCH family and introduced ARCH in mean (ARCH-M) in which they incorporated the conditional variance to describe volatility impact on the rate of return.

Despite the usefulness of the symmetric GARCH models in modeling the relation between conditional variance and asset's risk, Nelson (1991) criticizes the model by stating three major drawbacks; First, GARCH models do not take into account the negative correlation between current returns and future return volatilities. GARCH models determine the feature of the squared standard deviation by considering only the magnitude and not the positivity or negativity of unpredictable excess returns. The second limitation is the non-negativity constraint in which it creates difficulties in estimating the GARCH model. And finally, the author states the third drawback concerning the persistence of shocks to conditional variance.

Hence, Nelson (1991) proposed an asymmetric GARCH model that has the flexibility that allows the measurement of volatility changes in response to both positive and negative changes in asset's returns, in addition to the measurement of volatility cluster. EGARCH model also relaxes the non-negativity constraint by parameterizing the logarithm of the conditional variance (Elyasiani, et al. 2017). Moreover, due to information asymmetry, on the rate of return GJR-GARCH, TGARCH and many more models were introduced.

Distinct approaches have been used aiming at modeling the variation of exchange rates and their volatility since they have many implications on the economy of a country. These approached are the Generalized Autoregressive Conditional Heteroscedastic (GARCH), Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH), Ding, Granger and Engle-Generalized Autoregressive Conditional Heteroscedastic (DGE – GARCH), asymmetric power ARCH (APARCH), Integrated-GARCH (IGARCH) and several more.

Kutu & Ngalwa (2017) carried out a study employing both symmetric (GARCH (p, q)) and asymmetric (EGARCH (p, q)) models. These two alternatives are used to show a robust way to model exchange rate volatility amongst global shocks. Moreover, the authors aim is to determine the difference between these two estimators. Their study employed monthly data spanning between 1994:1 and 2013:12. The variables taken into consideration are exchange rates of South African Rand against the US dollar, the lag of exchange rates, global oil prices, and international interest rates. Their result suggests that global shocks have negative impact on exchange rates due to the adverse effect of international interest rates and oil prices. Moreover, the EGARCH (p, q) outperform the GARCH (p, q) in modeling exchange rate volatility.

Similarly, Abdallah (2012) research aimed to stylize facts about exchange rate volatility clustering and leverage effect for nineteen Arab countries against US dollar. The data are daily observation of exchange rate return series spanning from January 1st 2000 to 19th of November 2011. The author employs both symmetric model (GARCH) and asymmetric model (EGARCH) in modeling exchange rate series. The author concluded that EGARCH (1, 1) was positive for leverage effect for all currencies except for the Jordanian Dinar which indicates that negative -shock causes higher conditional variance for the next period than a positive shock does with the same magnitude. Moreover, the author recommends the use of GARCH (1, 1) model when modeling exchange rate volatility due to its adequacy.

Olowe (2009) modeled the Naira/Dollar exchange rate volatility using monthly data spanning from January 1970 till December 2007 while using the GARCH (1, 1), GJR-GARCH (1, 1), EGARCH (1, 1), TS-GARCH (1, 1), and the APARCH (1, 1) in order to investigate the asymmetric properties and volatility clustering of the Nigerian exchange rates. All models employed exhibits a common result, which is the persistence of volatility. The TS-GARCH and APARCH models are found to be the best models as they have all the parameters of the variance equations being significant.

Bosnjak. et al (2016) tested the performance of variant GARCH models for the EUR/HRK and USD/HRK while using daily data within the period from 1997 till 2015. Their results indicated that the GARCH (2, 1) is the best fitted model for the EUR/HRK, while GARCH (1, 1) fits best the USD/HRK daily return volatility.

Extensive debates have been emerging concerning the potential influence of exchange rate volatility on many economic aspects including the welfare, international trade, economic competitiveness with the external sector, profitability, risk management, etc. Especially, posterior to the collapse of Bretton-wood, many debates occurred. Fixed rate regime supporter argued that flexible (floating) exchange rate regime depressed the volume of international trade in two different ways; first of all, floating exchange rate are unpredictable, therefore imports/exports were subjected to higher exchange rate risk, and as a result, traders will be less willing to be engaged in international trades. Second, a volatile exchange rate would prompt the government to set generalized or sectorial trade barriers in order to offset the destabilizing effects of exchange rate fluctuations. These effects did not reflect the true changes in prices, income, and other essential determinates of competitive advantage and International trade (Brada & Méndez, 1988). On the other hand, supporters of floating exchange regime argue that floating rates boost international trade and that exchange rate move in parallel with the changes of fundamentals of the trade (McKenzie, 1999). Hence, Theoretical literatures have distinguished two main hypotheses:

1) A negative hypothesis assuming that exchange rate volatility detriments international trade.
2) A positive hypothesis that supports the fact that exchange rate volatility encourages international trade.

Some studies suggest an ambiguous relationship between those two variables, exchange rate volatility and international trade. This fact is due to the adverse effect of exchange rate volatility for both exporters and importers since they are located on the opposite sides of the forward contract. In other words, when exchange rates are highly volatile, exporters tend to lose (gain) while importers benefits (loss) from a positive (negative) trade balance or when forward risk premium is positive (negative) (Altintaş et al., 2011).

However, debates are still going on till our days because there is neither consensus nor conclusive evidence among economist regarding what true effect exchange rate volatility has on the volume of international trade. Moreover, as mentioned earlier, theoretical conclusions are conditional on several factors that affect the volume of international trade. Theoretically, there are two types of traders; risk-averse traders who would rather trade domestically in order to avoid exchange rate volatility, while on the other hand, the risk-lovers who would seek to earn more profits by increasing the volume of international trade. In addition to other factors such as existence of forward market or not, adjustment cost, market structure, etc… Moreover, the results obtained also depend on the sample period chosen, method used to measure volatility, countries selected (whether developed, developing, or under-developed).

Many researchers have tackled the relationship between exchange rate volatility and exports in particular. Some studies' results suggested an inconclusive relationship between these two variables such as the followings:

Hasanov and Baharumshah (2014) conducted a research to investigate exchange rate volatility effect on exports for, transition economies, Belarus, Kazakhstan, Russia, and Ukraine using a GARCH-in mean model. The estimate of the Bivariate GARCH-BEKK model assumes a conditional normal distribution for errors. Their estimated equation for export was jointed with that of exchange rate process since using a disaggregated approach might suffer from aggregation bias. Their ultimate aim was to investigate the dynamic of the short and long-run relationship between the volume of exports, foreign income, prices and exchange rate uncertainty. They concluded that exchange rate risk was harmful for Belarus and Ukraine, while on the other hand it was indeterminate for Kazakhstan and Russia since such countries trade flows relies on fuels and lubricants.

Another study conducted by Klaassen, F. (2004) tried to explain the reasons why exchange rate effect on trade is hard to conclude while using time series analyses. The latter argues that there are other unobserved export determinants that can obscure the true effect of exchange rate risk on trade. Therefore, the significance of risk on trade is inconclusive (positive or negative), and this due to three possible reasons argues the author; first, because exchange rate can be hedged by firms. Second, it is due to methodological problems adopted in the empirical tests. And, finally, the wrong specification of trade model such as not taking lagged effects into account. Hence, the research investigates exchange rates effects on international trade while using aggregate U.S exports to other G7 countries such as France, Germany, Italy, Japan, Canada and the U.K starting from January 1978 until November 1996. They used daily exchange rates to build up a more accurate monthly volatility and the used an autoregressive of order two (AR (2)) forecasts multi-month-ahead risk. Then they used Poisson lag structure to enhance the model dynamics. Klaassen, F. concluded that exchange rate risk appears to be constant over the long-run due to short-term fluctuation.

Moreover, a study conducted by Ramali and Podivinsky (2010) to investigate the effect of bilateral exchange rate volatility and exports between five ASEAN countries, namely Singapore, Malaysia, Philippine, Indonesia, and Thailand, and the United State. Their literature illustrates that exchange rate volatility might have a negative or positive effect on export depending on market agents. However, if the agents are risk-averse, then, the impact would be negative, and that impact is shown either directly through uncertainty and adjustment cost or indirectly through government policies and resources allocation. The authors investigated the long-run and short-run relationship between exchange rate volatility and exports using the Granger causality test utilizing error correction framework and Johansen Juselius test. Their results show that the real bilateral exchange rate volatility was significantly positive for Indonesia and negative for both Philippine and Singapore, and ambiguous for Malaysia and Thailand.

The stability of exchange rate fluctuation is the main concern of many large and emerging countries in order to mitigate the influence of exchange rate risk. Therefore, Aftab, M. and Rehman, I. (2017) conducted a study that aims to examine the influence of exchange rate on international trade (Exports and Imports) using industry –level disaggregated data for Malaysia and Singapore while using Autoregressive Distributed Lag method (ARDL). This method is quite suitable and effective for the issue of Mix Case of series integration. Moreover, in order to avoid aggregation bias due to the use of low-frequency samples, the authors used monthly data while monitoring the nexus between exchange rate fluctuations and industry-level bilateral trade flow, for a period spanning from the year 2000 till the year 2014. Their result suggests that exchange rate risk influence varies between industries for different period of time. Some industries are affected for the long-run whilst other industries are influenced for the short-run.

Aristotelous (2001) conducted a research aiming at investigating the impact of exchange rate volatility and exchange rate regime on British Exports to the United State for a quite lengthy period spanning from 1889-1999 in order to capture the impact of various exchange rate regime (Fixed, floating and managed-float exchange rate regimes) on exports volume. The author used a generalized gravity model because it has the capability to explain the volume of trade between countries in a consistent way. Two main points where extracted from this study; first, exchange rate volatility has no impact on British exports to the U.S and secondly, exchange rate regimes have also no impact on the British export volume to the U.S.

On another note, some researchers have had claimed to witness a positive correlation between exchange rate volatility and export, such as the study of Altintaş, Cetin, & Öz, (2011) aiming to investigate the impact of exchange rate volatility on Turkish exports while using a quarterly observation starting from 1993:3 to 2009:4. They employed the ARDL co integration approach since it is efficient to capture long-run relationship between variable while using a limited sample data. They've also used the error correction model. Their results show that Turkish export is notably connected to foreign income as well to exchange rate volatility however it is not related to exported price. In other words, exchange rate volatility and foreign income affects positively Turkish exports while exports prices do not.

Also, Choudhry, (2008) research examined the emerging concerns regarding whether increased exchange rate volatility has an effect on international trade flows, since the adoption of flexible exchange rate regime. The research investigated specifically the effect of exchange rate volatility on United Kingdom imports from Canada, Japan, and New Zealand for a period spanning from 1980 to 2003 while adopting a multivariate co integration method and constraint error correction model. Moreover, the GARCH (1, 1) is used to determine exchange rate volatility. The author concluded that the volatility of exchange rate has a significantly positive effect on real import.

Some other researchers argue that an increase in exchange rate fluctuations will reduce the volume of exports. Chit, Rizov, & Willenbockel (2008) research had two main purposes, first was to distinguish the specificity of export between emerging East Asian and industrial countries, and to test to robustness of long-run relationship between exports and exchange rate volatility. The authors' studied the impact of bilateral real exchange rate volatility on real export between five emerging East Asian countries (China, Indonesia, Malaysia, Philippines, and Thailand) and thirteen industrial countries. They used quarterly data over a period expanded from 1982:Q1 until 2006:Q4 while employing a Panel unit root and co integration test in order to verify the long- run relation between exchange rate risk and export. Their research outcome suggests a significant negative impact for exchange rate volatility on the emerging East Asian countries' exports, however, the magnitude of this effect on the long-run is relatively small. The price competitiveness also plays a negative role on country's export to the designated market.

Aly & Hosni (2018) examined the nexus between exchange rate volatility and Egyptian non-petroleum export performance while using annual data that span from 1980 till 2016. The latter used two methods to measure exchange rate volatility; Moving average standard deviation and GARCH model. Their results show a negative correlation between exchange rate volatility and the real value of non-petroleum exports for the long run.

Sugiharso (2017) investigated the impact of exchange rate volatility on Indonesian nonoil exports to three of Indonesia's main trade partner, namely the United States, Japan, and China. The research used aggregated and disaggregated data since the year 1996 till 2014. Export equation was estimated using Seemingly Unrelated Regression. Their results shows that exchange rate volatility has a negative impact of Indonesian exports, however the results may vary among industries in the countries under investigation.

2.3 Conclusion

Many researchers have modeled exchange rate volatility using various types of ARCH and GARCH models in order to provide a better understanding of high-frequency data. Moreover, examining the proposed models enables the determination of volatility characteristics. The accurate measurement of exchange rate volatility is considerably vital, especially for the case of the U.K. Since the announcement of the referendum, the value of pound fluctuated remarkably which made Brexit a real issue rather than just a national concern.

Exchange rates dynamics have multiple implications for the domestic and international economy, hence, a broad literature is available that explores the various aspect of it. One of these implications is the impact of exchange rate over the exports of a country. The U.K depends heavily on exports by 62 % of their total GDP, where 47% of U.K's exports are directed to the EU. Therefore, the ambiguity about future trade relation between EU and U.K induces more uncertainty in the market. Numerous studies have explored the impact of exchange rate volatility on exports; some studies reveal a positive correlation whilst other studies demonstrate a negative correlation, yet no consensus or conclusive evidences are available.

From this perspective, the present work is intended to assess the characteristics of GBP/EUR exchange rate while using both symmetric and asymmetric models (i.e. EWMA, GARCH (1, 1), and EGARCH (1, 1)), in order to understand the effect of Brexit (shock) on the exchange rate volatility. Moreover, this research attempt to link the variation of GBP/EUR exchange rates to U.K's exports to Euro zone countries and detect whether this variation is positively or negatively correlated. This link is demonstrated using a Regression Model using the chow test.

Subsequently, chapter 3 will elaborate the adopted methodology. The descriptive statistics of GPB/EUR exchange rates returns are set forth. The characteristic of the chosen models, EWMA, GARCH (1, 1), and EGARCH (1, 1) will be elaborated in details. Also, the regression analysis using the Chow test will be explained.

CHAPTER 3

PROCEDURES AND METHODOLOGY

3.1 Introduction

Exchange rates, in general, is a primary financial element linking the domestic economy with other countries worldwide. The value of a domestic currency and the volatility of exchange rates influence the economic agents' investments and consumption decision making. High exchange rate volatility can have diverse impact via numerous channels, namely exports (Noria et al., 2019). Exchange rate is a key element for U. K's trading economy for multiple purposes. First, exchange rates fluctuation represents risk to firms holding assets in currencies other than Sterling. It also represents a cost for firm paying commission on the exchange of one currency for another. And finally, exchange rates affect the price of exports and the price of imports, hence the balance of payments.

Certainly, Brexit represents a significant shock to the U. K's economy. Specifically, the process of Brexit could have an effect either on the short-term on the financial market and on exchange rates or on the long-term due to the increasing barriers on trade, labor and capital mobility depending on scenario options that the country will adopt. Chapter 2 presents numerous studies available that elucidates the relationship between a fluctuated exchange rates and the volume of exports. The results are yet diverse, some studies demonstrate a positive impact whilst other exhibits negative impact. However, the link between exchange rate volatility and exports remains inconclusive. Chapter 2 also sets out studies using the most common models for modeling exchange rates volatility, notably the EWMA, GARCH (1, 1) and the asymmetric EGARCH (1, 1) models.

From this perspective, the ultimate purpose of our study is to answer the following questions:

1) Which of the adopted models EWMA, GARCH (1, 1), and EGARCH (1, 1) fit best the volatility assessment of GBP/EUR exchange rates?
2) Has the volatility structure of GBP/EUR exchange rates changed post-Brexit referendum?
3) Does a fluctuated GBP/EUR exchange rate affect U. K's exports to Euro zone countries as a response to Brexit referendum?
4) Is there any structural break following the Brexit referendum?

To answer this research questions, the methodology adopted starts with estimating the parameters of the chosen model namely, EWMA, GARCH (1, 1), and the asymmetric EGARCH (1, 1) models, followed by determining the optimal model for GBP/EUR exchange rates volatility while adopting the three-error metrics, namely: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Subsequently, testing the changes in GBP/EUR exchange rates volatility post the announcement of EU referendum is examined. The methodology consists of adding a dummy variable to our optimal model. This dummy variable enables to detect changes in exchange rate volatility between two distinguished periods, it takes a value of 0 for stable period (pre-Brexit) and value of 1 for unstable period (post-Brexit). A significant dummy variable suggests that the Brexit announcement had an impact on exchange rate volatility. Then, to determine the relationship between U. K's exports to Eurozone and the changes in GBP/EUR exchange rates volatility, this research employs the Autoregressive Distributed Lag (ARDL) regression model. Finally, the Chow test is used to test whether Brexit had caused a structural break in GBP/EUR exchange rates volatility.

3.2 Data and Variables

The first part of this research employs GBP/EUR daily exchange rates that are extracted from Thomson Reuter's database for the period spanning from January 1st, 2010 till August 31st, 2020 totaling 2,782 daily observations. While the second part employs monthly data for U. K's weighted average Industrial Production index (IPI), Real effective exchange rate (REER), Commodity term of trade (TOT), and GBP/EUR monthly volatility, and U. K's Exports to Eurozone Countries namely, Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherland, Portugal, Slovakia, Slovenia, and Spain for a period starting from January 2010 till August 2020 totaling 128 monthly observations. These data are retrieved from the IMF database.

We use returns to denote price changes over the data used at the end of day *t* and at the end of day *t-1*.

Daily return is denoted by u and is calculated as:

$$u = \frac{S_t - S_{t-1}}{S_{t-1}} \tag{Eq.01}$$

Where:

S_t: Denotes the daily closing value on day *t*.

S_{t-1}: Denotes the daily closing value on day *t-1*.

Figure 1 displays the daily returns of GBP/EUR exchange rate time series. From this figure, we can observe the volatility clustering.

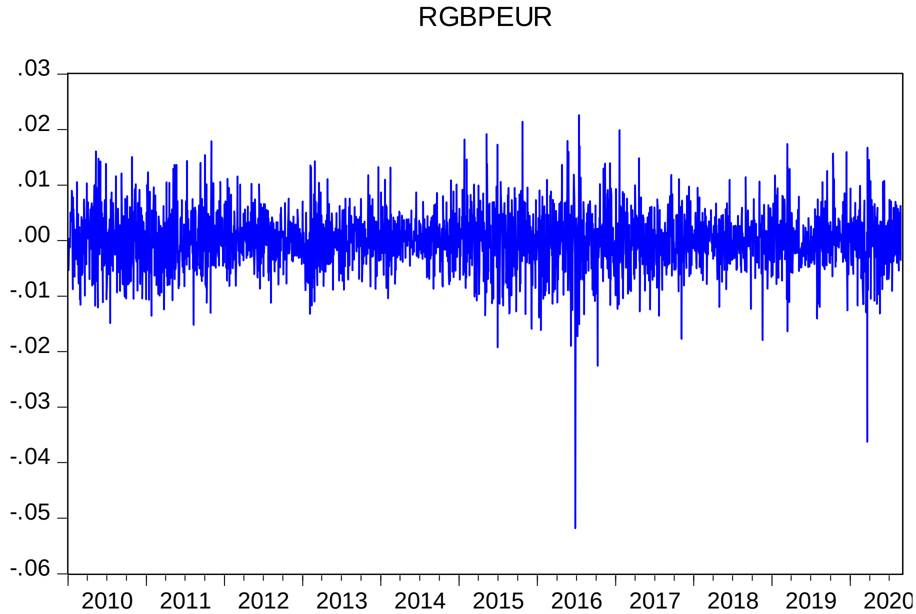

Figure 1. The GBP/EUR Daily Return Time Series.

Figure 2 shows the daily returns of the GBP/EUR exchange rates with its descriptive statistics. The mean daily return for the GBP/EUR exchange rate was 0.0013% with a standard deviation of 0.5240%. The minimum return was -5.1813% while the maximum was 2.2640%. The daily returns exhibit excess kurtosis, implying that the distribution is not normal. The Jarque-Bera null hypothesis of normal distribution is rejected since its p-value 0.000.

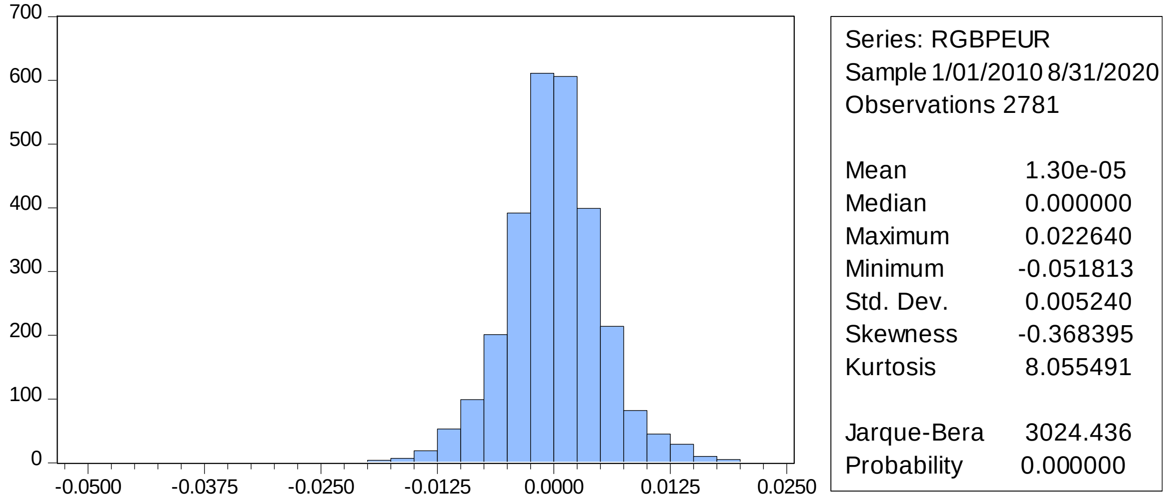

Figure 2. Descriptive Statistics of GBP/EUR Daily Returns.

To examine the impact of exchange rate volatility on exports, this study adds the exchange rate volatility to the export demand function. Although previous studies have used consumer income (GDP) as one of the main factors affecting export demand, this study will use Industrial Production Index (IPI) as a proxy for GDP sine IPI is available on a monthly basis, while GDP is available only on quarterly basis. The variables included in the export demand function are as follows:

A. The Industrial Production Index (IPI):

The industrial production index (IPI) is an important indicator in macroeconomic since it is considered as a leading indicator of Gross Domestic Product (GDP) growth and economic performance due to its sensitivity to consumer demand and interest rates. IPI measures the output of the industrial sector which comprises mining, manufacturing, utilities, and constructions. As mentioned previously, this measure is included as proxy of GDP since IPI is available on a monthly data whereas GDP is only available on quarterly basis. Referring to our model, we employ the weighted average IPI for eurozone countries, which is calculated as the sum of each country's IPI multiplied by its weight in relation to U.K trading volume.

B. Real Effective Exchange Rate (REER):

The real effective exchange rate (REER) is the weighted average of a country's currency in relation to an index of major other currencies (i.e., U.S dollars, Euro, Pound, etc..). Weights are determined by comparing the trade of balance of the country's currency against each country within the index. REER is an important element for trade assessment and is measured in such a manner that an increase reflects an appreciation of the British pound. Thus, an increase in REER implies a loss in trade competitiveness since the exports become more expensive.

C. Commodity Term of Trade (TOT):

The commodity term of trade is calculated by dividing the commodity Export Price Index by commodity Import Price Index, then multiplied by 100. When country's TOT is less 100%, then imports are more expensive than exports. When country's TOT exceeds 100%, then exports are more expensive than imports.

D. GBP/EUR Volatility (VOL):

Exchange rate volatility denotes the amount of uncertainly or risk about the change in exchange rate. A larger range of values in a short time span is termed high volatility. A low volatile exchange rate is one that does not fluctuate dramatically. However, there is no dominant approximation for volatility. Exchange rate volatility will be estimated using the optimal model (EWMA, GARCH (1,1) and EGARCH (1,1)).

Table 1 displays the descriptive statistics (the mean, median. Standard deviation, skewness, kurtosis, and the Jarque-Bera test) of our dependent and independent variables daily returns. All tests are performed using EVIEWS 10. Looking at skewness, a value between -0.5 and 0.5 suggest a symmetrical and a normal distribution, while an absolute value between 0.5 and 1 indicates a moderately skewed data. Hence, LIPI, LTOT and GBPEUR are normally distributed with a skewness of -0.288, -0.208, and -0.267 respectively. However, LEX is negatively skewed and LREER is positively skewed with skewness of -0.907 and 0.898 respectively. The Jarque-Bera tests confirm the obtained results where LIPI, LTOT, and GBPEUR are normally distributed with p-values greater than 0.01, while LEX and LREER are not normally distributed with p-values less than 0.01.

Descriptive Statistics

Variables	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque - Bera	Probability	Observ -ations
LEX	9.678	9.699	0.120	-0.907	4.784	34.529	0.000	128
LIPI	4.656	4.641	0.056	-0.288	3.267	2.146	0.342	128
LREER	4.626	4.608	0.051	0.898	2.913	17.250	0.000	128
LTOT	4.587	4.588	0.016	-0.208	2.054	5.698	0.058	128
GBPEUR	0.000	-0.001	0.022	-0.267	3.446	2.565	0.277	127

Table 1. Descriptive Statistics for the selected variables.

As per Sugiharso (2017), we specify the model of export demand function as follows:

$$LnEX_j^k = \alpha_0 + \alpha_1 LIPI_t^k + \alpha_2 LREER_t + \alpha_3 LTOT_t + \alpha_4 LVOL_t + \varepsilon_{it} \qquad \text{(Eq.02)}$$

Where:

$LnEX_j^k$ is the real export volume from country *j* to *k*,

$LIPI_t^k$ is the Weighted average Industrial Production Index for country *k* measuring foreign income,

k = Eurozone Countries,

$LREER_t$ is the real effective exchange rate,

$LTOT_t$ is the commodity term of trade,

$LVOL_t$ is the GBP/EUR exchange rate volatility.

All variables are in natural logarithm form since Khan and Ross (1977) advocate the use of a log-linear specification rather than a standard linear one on both empirical and theoretical grounds. The rationale is that the former form allows the dependent variable to react proportionally to a change in the regressors. As for the sign of the coefficients, we have the following expectations. First, an increase in the industrial production of trading partners would be expected to increase the volume of exports to those partners, hence $\alpha_1 > 0$. Second, the real effective exchange rate may decrease the volume of export due to relative price effect, thus $\alpha_2 < 0$ (Thi Thuy, 2019). Third, a higher TOT indicates an increase in the price of export as compared to the price of imports, subsequently the country is expected to increase its imports for the same volume of exported products, which might indicate a negative relationship between the volume of exports and TOT, so $\alpha_3 < 0$. Finally, the relationship between exchange rate volatility and export is ambiguous, hence $\alpha_4 > 0$ or $\alpha_4 < 0$.

Measuring the correlations between the dependent variables and the independent variables is vital when exploring the relationship between two different time series. Therefore, we measure the correlation between the IPI, REER, TOT and GBP/EUR exchange rate volatility. The simple correlation measurement is executed using EVIEWS 10. As per table 2, we can observe a negative relationship between LIPI and LREER, between LIPI and LTOT, between LREER and LVOL, and between LTOT and LVOL. While, on the other hand, we observe a positive relationship LREER and LTOT, and between LVOL and LIPI.

Variables Correlation Test

Variables	LIPI	LREER	LTOT	LVOL
LIPI	1.000	-0.042	-0.518	0.215
LREER	-0.042	1.000	0.261	-0.083
LTOT	-0.518	0.261	1.000	-0.433
LVOL	0.215	-0.083	-0.433	1.000

Table 2. Correlation Measurement between independent variables.

The following sections present a description of the adopted approaches to model the GBP/EUR exchange rate volatility, explain the Autoregressive Distributed Lag (ARDL) used to determine the relationship between exchange rate volatility and exports, and explore the Chow test utilized to detect the presence of a structural break in the relationship between our dependent and independent variables after the Brexit Referendum.

3.3 Volatility Models

3.3.1 Exponentially Weighted Moving Average Model (EWMA):

The simple volatility and historical volatility models have exhibited weakness in terms of allocating weights to past observations, as a response, the EWMA model has been developed. This approach track changes in the volatility under the assumption that asset returns are symmetrical and independently distributed. It utilizes two fundamental parameters to conduct its calculations, time, and lambda (λ). Lambda (λ) is the decay factor, also known as the smoothing parameter; it is the coefficient that assigns the correlation of the predicted volatility to past data. A lower value of λ leads the volatility of the upcoming day to be highly volatile, while a higher value of λ produces estimates that respond slowly to new information provided by the daily percentage change. In other words, the EWMA approach devotes more weights for recent information rather than older news, therefore the weights decrease exponentially as they move back through time.

The value of Lambda varies between 0 and 1; thus, RiskMetrics application developed by JP Morgan recommends that the value of lambda to be set equal to 0.94 for daily data and 0.97 for monthly data (Kayahan et al., 2014).

The EWMA formula is represented as follows:

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2 \qquad \text{(Eq.03)}$$

Where:

σ_n^2 : The volatility to day n.

σ_{n-1}^2: The first volatility lag.

u_{n-1}^2 : The most recent daily percentage change.

λ: the smoothing coefficient.

From equation (Eq.03), the current conditional variance σ_n^2 is dependent on two main components; $\lambda\sigma_{n-1}^2$which capture the persistence in the volatility, and $(1-\lambda)u_{n-1}^2$ which caters the intensity of the variance as a response to market news.

3.3.2 The Generalized Autoregressive Conditional Heteroskedastic GARCH (1, 1) Model:

Modeling the volatility as suggested by Engle (1982) by using the conditional heteroskedastic regression with autoregressive conditional heteroskedasticity (ARCH) model requires estimating many parameters to predict the volatility, hence, lag length needed are large. Bollerslev (1986) and Taylor (1986) proposed the GARCH (p, q) model that enables the conditional variance to be dependent on its own previous lags and capture information contained in historical values of the variance. This typically reduces the number required of ARCH lags when estimating the volatility (Abdullah et al., 2017).

The GARCH (p, q) framework is expressed by allowing the current conditional variance to be dependent on first p past conditional variance and q past squared innovations. The GARCH (p, q) equation is as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j u_{n-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 \qquad \text{(Eq.04)}$$

Where “p” is number of lagged conditional variance (σ^2) and “q” is the number of residual returns (ε_t).

The mean equation is given by $r_t = \mu + \varepsilon_t$. The financial time series return at time *t* is referred to as r_t, returns mean value is denoted as μ, and ε_t is the innovation term (or previous shocks) also known as the error term.

ε_t is defined as:

$$\varepsilon_t = \sigma_t z_t \qquad \text{(Eq.05)}$$

Where z_t represents the standardized residual returns $iid{\sim}(0{,}1)$ and σ_t^2 denotes the conditional variance (Omari et al., 2017).

The GARCH (1, 1) model is the most communally used approach in the financial literature. The notation of GARCH (1, 1) model is the following:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \qquad \text{(Eq.06)}$$

Setting $\omega = \gamma V_L$ knowing that V_L is the average long-run variance and γ is the weight assigned to it.

γ can be calculated as:

$$\gamma = 1 - \alpha - \beta \quad \text{(Eq.07)}$$

And the long-run variance V_L can then be computed as:

$$V_L = \omega / \gamma \quad \text{(Eq.08)}$$

Hence, GARCH (1, 1) model equation can be expressed as:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad \text{(Eq.09)}$$

α and β are also weights assigned to u_{n-1}^2 and σ_{n-1}^2 respectively. Where α implies that the volatility reacts significantly to market movements while β indicated the persistence of shocks. The sum of lagged variance weight (α) and lagged squared return weight (β) are known as persistence.

To ensure the stability of the model, some restrictions need to be imposed: $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$ and the sum of all weights (i.e., ω, α, and β) should be equal to 1. However, if $\alpha + \beta > 1$ then in this case GARCH (1, 1) is considered unstable; therefore, it exhibits slow decay towards the mean (i.e., the persistence is not strongly mean reverting). If $\alpha + \beta < 1$, this indicates that the persistence is strongly mean reverting; it exhibits rapid decay towards the mean. It also indicates that the variance is positive, and the series is stationary.

In varied cases, GARCH (1, 1) model is counted as a reasonably good model for estimating conditional volatility and analyzing financial time series due to its simplicity and robustness among other volatility models. Hence, GARCH (1, 1) is considerably sufficient to capture the volatility clustering in data (Epaphra, 2017). However, GARCH (1, 1) has multiple limitations, noting its inability to accommodate to asymmetric changes in financial data, furthermore, the GARCH (1, 1) fails to account for leverage effect.

The EWMA model is a particular case of GARCH (1, 1) where γ is equal to zero, α is equal to (1-λ), and β is equal to λ (Naimy, 2013). Both EWMA and GARCH (1, 1) employs exponential smoothing, yet the only advantage that GARCH (1, 1) has is that it incorporates the parameter that weights the long-run average; hence it considers mean reversion, therefore theoretically, GARCH (1, 1) is more attractive than the EWMA model (Hull, 2012). In cases where ω is negative, switching to EWMA model is more appropriate since the GARCH (1, 1) is proved to be unstable (Naimy, 2013).

3.3.3 The Exponential Generalized Autoregressive Conditional Heteroskedasticity Model (EGARCH):

The structure of the GARCH (1, 1) model suggests that the shock in ε_{t-1} has the same impact regardless of whether ε_{t-1} is positive or negative. In fact, it is known that negative shocks to the system generate greater volatility than positive shocks with the same magnitude. Hence, aiming at resolving the asymmetry in financial data, Nelson (1991) introduced the exponential generalized autoregressive conditional heteroskedasticity model (EGARCH) (Abdullah et al., 2017).

The logarithmic nature of the EGARCH model ensures that even in cases where the estimated parameters are negative, the conditional variance remains positive (Osei-Assibey, 2015). The general form of EGARCH (p, q) model can be expressed as:

$$\log h_t = \alpha + \sum_{J=1}^{P} \beta_J \, log h_{t-j} + \left(\sum_{i=1}^{q} \omega_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}}\right) + \left|\sum_{i=1}^{q} \lambda_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}}\right| \qquad \text{(Eq.10)}$$

Where $\log h_t$,$log h_{t-j}$, and ε_{t-i} are the logarithm conditional volatility, the logarithm of the first lag in conditional volatility, and the error term at time i, respectively. A non-zero value of the parameter ω_i signalizes asymmetry. If $\omega_i < 0$ is observed in financial markets, then leverage effect is present. Hence, the next trading day volatility increased due to the previous day's negative residuals. If $\omega_i > 0$ is observed, then in this case positive shocks generate more volatility than negative news.

The simplest form of EGARCH (1, 1) model is given by:

$$\ln(\sigma^2{}_t) = \omega + \beta_1 \ln(\sigma^2{}_{t-1}) + \gamma_1 \frac{u_{t-1}}{\sqrt{\sigma^2{}_{t-1}}} + \alpha_1 \left[\frac{|u_{t-1}|}{\sqrt{\sigma^2{}_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] \qquad \text{(Eq.11)}$$

Where:

p=1: the order of ARCH component model

q=1: the order of GARCH component model

ω: Time-independent parameter

α_1: A parameter that represents magnitude effect.

β_1: A GARCH component model parameter to measure persistence in conditional volatility irrespective of market news.

γ_1: A parameter that measures asymmetry / Leverage effect.

u_{t-1}: Recent daily percentage returns on day t-1

$\sigma^2{}_t$: Conditional Variance. This is an estimate of Variance made on a one-period ahead

$\sigma^2{}_{t-1}$: The previous day variance.

Moreover, EGARCH (1, 1) considers the volatility clustering. In other words, this model captures the fact that large movements are followed by large movements suggesting that past shocks/news are persistent. If volatility was high at *t-1*, hence it will also be high at time *t*. If for instance something bad or good happened in the market the previous day, its impact is persistent the following day and will be reflected in the variance at time *t* (Elyasiani et al., 2017).

Furthermore, it is devised to capture leptokurtic returns, which is when the unconditional distribution of financial time series returns form an excess Kurtosis. When β is high, this means that volatility caused by a crisis for example will not be eliminated in the short run. If | β |<1 then the model is stationary and has a finite kurtosis (Kun, 2011). If β =1 then the model is integrated. If β>1, then the variance is unstable and the EGARCH (1, 1) will have undesirable properties.

Another commonly used form of the EGARCH (1, 1) process is:

$$log\ \sigma_n^2 = \gamma v_l + \beta g(z_{n-1}) + \ \alpha log \sigma_{n-1}^2 \qquad \text{(Eq. 12)}$$

The $\beta g(z_{n-1})$ function interprets the presence of leverage effect.

3.4 Optimal Model Selection

The best-fitted model is selected based on the three-error metrics: The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These error metrics determine the best model by subtracting the calculated volatility for each model from the realized volatility. The model that obtains the least errors will therefore be ranked first.

These error statistics are defined as:

$$RSME = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(y - \hat{y}_t)^2}$$

$$MAE = \frac{1}{m}\sum_{t=1}^{m}|y - \hat{y}|$$

$$MAPE = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{y-\hat{y}}{y}\right| * 100$$

Where:

m= number of periods.

$\hat{y}$= the fitted value in time *t* (calculated volatility i.e., EWMA, GARCH (1, 1), AND EGARCH (1,1) volatility).

y= the actual observed value in time *t* (realized volatility). The realized variance is calculated based on the returns sum squared. The formula of the realized volatility σ_n is defined as follows:

$$\sigma_n = \sqrt{\sum_{i=1}^{N} u_i^2}$$

Where u_i is the return on day *i*, and *N* is the number of observations, which is 10 days. The realized daily volatility will be calculated in Excel and converted into yearly volatility by multiplying it by square root of 250.

3.5 Changes in volatility Structure

To answer our second research question, whether the volatility structure of GBP/EUR exchange rates has changed post-Brexit referendum, we use the selected optimal model and add a dummy variable. This dummy variable is supposed to provide information on the changes in the volatility of GBP/EUR exchange rate volatility between two distinguished periods, mainly through the level of significance of its parameter and through its sign. The dummy variable takes the value of 0 for pre-Brexit referendum period (Jan 1, 2010 until June 23, 2016) and 1 for post-Brexit referendum (June 24, 2016 until August 31, 2020). The parameter sign determines if the volatility of GBP/EUR exchange rates has changed in response to Brexit referendum or not. A negative and significant sign indicates a decrease in the volatility of GBP/EUR exchange rates, whereas a positive and significant coefficient indicates an increase in the volatility of GBP/EUR exchange rates. If the parameter fails to be significant, then this methodology will not be able to provide the required information to answer our research question. Scivoletto (2019) performed the same methodology along with others to detect whether Brexit referendum have caused a structural change in GBP/EUR volatility.

3.6 The Autoregressive Distributed Lag (ARDL):

To answer our third research question, whether the volatility of GBP/EUR exchange rate affected U. K's exports to Euro zone countries, the Autoregressive Distributed Lag (ARDL) is used. The ARDL models have been used for decades and they have been recently shown their superiority for testing the presence of long-run relationships between time series. The stationarity of the data is essential when modeling the relationship between different time series. If encountered, the simplest solution is taking the first difference of the series and estimating a standard regression model. However, this method may result in ambiguous outcomes due to the loss of meaningful information. In 1980, Engle and Granger developed a co-integration model that can detect the presence of a single co-integration vector. Further, Johansen (1988) revised this approach and enabled researchers to test the presences of more than one co-integration vector under the conditions that time series should not be stationary at levels and they should be co-integrated at the same order. Pesaran et al. (2001) have developed the bound test approach to surpass this problem. Based on this approach, regardless of whether time series are at I (0) or I (1), co-integration relationship can be tested (Thi thuy et al., 2019).

Exchange rates volatility measure are mostly stationary, while trade models are non-stationary. Hence, the Autoregressive Distributed Lag (ARDL) approach developed by Pesaran et al. (2001) is the most suitable to investigate the effect of GBP/EUR exchange rate volatility on U. K’s exports to Eurozone, similar to many studies that employed ARDL to investigate the relationship between exchange rate volatility and exports (Thi Thuy, et al., 2019; Sugiharti, et al., 2020; Bahmani-Oskooee, et al., 2017; Serenis, et al., 2014; and Srinivasan, et al., 2012).

The ARDL model is an ordinary least square (OLS) based model applicable for non-stationary time series and for data with different levels of integrations (Shrestha et al., 2018). As previously explained, the former surpasses other model by its capability to investigate the relationship between time series with mixed co-integration levels (Thi thuy et al., 2019).

ARDL model has several advantages over other cointegration models such as Engle and Granger (1987) and Johansen and Juselius (1990):

- It can be applied whether the variables are not integrated of the same order, while Johansen cointegration techniques require that all the variables in the system be of equal order of integration.
- The ARDL test is more efficient in the case of small and finite sample data while the Johansen cointegration techniques require large data samples for validity.
- ARDL allows for a simple error correction model that provides short-run coefficients without losing long run coefficients.
- ARDL allows for a different order of lag without affecting the distribution of the test statistic (Pesaran et al, 2001).

In its basic form, the error correction ARDL model is given by:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \theta_{1i} \Delta y_{t-i} + \sum_{i=1}^{p} \theta_{2i} \Delta x_{t-i} + \sum_{i=1}^{p} \theta_{3i} \Delta z_{t-i} + \lambda_1 y_{t-1} + \lambda_2 x_{t-1} + \lambda_3 z_{t-1} + u_t \qquad \text{(Eq.13)}$$

Short-run dynamics are represented in the first part of this equation by θ_{1i}, θ_{2i}, and θ_{3i}. The long-run dynamics are represented by λs in the second part of this equation. The null hypothesis is: $\lambda_1 + \lambda_2 + \lambda_3 = 0$. This indicates the nonexistence of long-run relationship (Shrestha et al., 2017).

The model is autoregressive because y_t is explained by its lagged value. It also has a distributed lag component in the form of successive lags of the explanatory variables.

The methodology follows several steps:

- In the first step, we test for a unit root test using Phillips-Perron test, with the null hypothesis that the variable contains a unit root (i.e., not stationary). The ARDL test assumes that all variables are I (0) or I (1) and none of them are I (2). Thus, the main objective is to ensure that none of the variables are I (2), otherwise, ARDL cannot be used.
- In the second step, we determine the appropriate lag structure of the equation based on the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SC), and the Hannan and Quinn information criterion (HQ).
- In the third step, a particular ARDL model is formulated based on the optimal lag structure, as follows:

$$\Delta LEX_j^k = \alpha_0 + \lambda_1 LEX_{t-1} + \lambda_2 LIPI_{t-1} + \lambda_3 LREER_{t-1} + \lambda_3 LTOT_{t-1} + \lambda_4 LVOL_{t-1} + \sum_{i=1}^{l_1-1} \theta_{1i}\, \Delta LIPI_{t-i}^k + \sum_{i=1}^{l_2-1} \theta_{2i}\, \Delta LREER_{t-i} + \sum_{i=1}^{l_3-1} \theta_{3i}\, \Delta LTOT_{t-i} + \sum_{i=1}^{l_4-1} \theta_{4i}\, \Delta LVOL_{t-i} + \varepsilon_{it} \quad \text{(Eq.14)}$$

Then, we run several diagnostic tests, such as LM test to check whether the errors are not serially dependent, Jarque-Bera to check whether the errors are normally distributed and Breusch-Pagan-Godfrey to test whether errors are homoscedastic.

- In the fifth step, the stability of the model is assessed using cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) (Stamatious and Dritsakis, 2014). If the plots stay within the critical bonds, then we cannot reject the null hypothesis of all coefficients in the given regression is stable.
- In the sixth step, the bound test is performed for testing the presence of a long run relationship between the variables. The null hypothesis is no cointegration among variables, or the long-term coefficients are equal to zero. Thus, a rejection of the null implies the presence of a long run relationship. The F-test has two critical value bounds depending whether variables are I (0) or I (1). The upper bound (lower) assumes that all variables are integrated of order one (zero). If the F-value is above the upper bound, we conclude that there is a cointegration, whereas a F-value below the lower bound suggests

no cointegration. However, a F-value between the two bounds suggests that the test is inconclusive.

- In the seventh step and depending on the bound test results, either ARDL model (assuming no cointegration) or Error Correction Model (in case of cointegration) is run. In case of cointegration, the long run relationships between variables are estimated using Equation (15):

$$LEX_t = \alpha_0 + \lambda_1 LEX_t + \lambda_2 LIPI_t + \lambda_3 LREER_t + \lambda_3 LTOT_t + \lambda_4 LVOL_t + \epsilon_t \qquad \text{(Eq.15)}$$

Then, Error Correction Model (ECM) is derived from the ARDL as follows:

$$LEX_t = \alpha_0 + \sum_{i=1}^{l_1-1} \theta_{1i}\, \Delta LIPI_{t-i}^{k} + \sum_{i=1}^{l_2-1} \theta_{2i}\, \Delta LREER_{t-i} + \sum_{i=1}^{l_3-1} \theta_{3i}\, \Delta LTOT_{t-i} + \sum_{i=1}^{l_4-1} \theta_{4i}\, \Delta LVOL_{t-i} + \varepsilon_{it}\beta_1 ECM_{t-i} + \epsilon_t \qquad \text{(Eq.16)}$$

Where ECM_{t-1} is the error term that should be negative and significant, indicating the speed of adjustment or how quickly variables return to their long run equilibrium.

- In the last step, the results of the regression estimated in the previous step are analyzed.

3.7 The Chow Test:

As explained earlier, to answer the fourth research question, the Chow test is performed while employing monthly data spanning from January 2010 until August 2020. This is referred to as the pooled data. The pooled data is then divided into two sub-samples. The pre-structural break data starts from January 2010 until June 2016 while the post- structural break data starts from July 2016 until August 2020. A linear regression, in statistical modeling, has been widely applied to test the relationship between a dependent variable and one or more independent variable. When a linear regression is applied, the question that often arises as whether the correlation remains stable after witnessing a violent change or sudden shock to the market, or whether the same relationship exists between two different groups of economic units. Economically speaking, it is irrational to assume that two relationships are the same in two periods, or for two groups. It may occur that only parts of the relationship are identical (Chow, 1960).

In fact, a series of data, or cross-sectional data may exhibit a structural break due to a sudden change in the relationship being examined. Such changes include a serious disaster, war, policy changes, etc. Gregory Chow (1960) introduced the Chow test, which is a tool that can determine whether a single regression is more efficient than two separate regressions, under the assumption that the disturbance term is the same in both sub-samples. The latter is preferable compared to other similar approaches due to its computational simplicity. The chow test in effect utilizes the F-Test. Figure 3 of case no.1 and case no.2 illustrates the presence of structural break in the data.

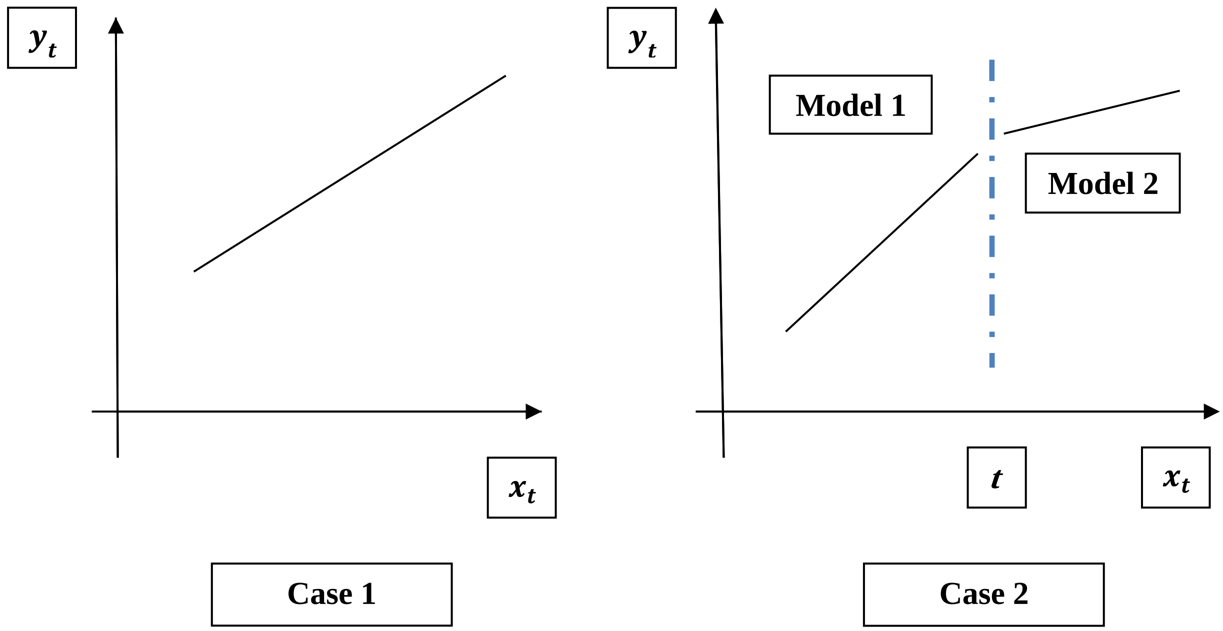

Figure 3. Presence of structural break.

Case no.1 presents a single regression line that fit the scatterplot of data. It is be expressed as:

$$y_t = \alpha_0 + \alpha_1 x_t + \varepsilon_t \qquad \text{(Eq.017)}$$

Case no.2 exhibits the data, where there is a structural break. We have two separate models expressed as:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_{1t} \qquad \text{(Eq.018)}$$

And

$$y_t = \delta_0 + \delta_1 x_t + \varepsilon_{2t} \qquad \text{(Eq.013)}$$

Where x_t is the explanatory variable, β_1 *and* δ_1 are column vectors of K regression coefficients and y_t are column vector for dependent variable. ε_t is the stochastic term that is assumed to be normally distributed with zero mean and variance covariance matrix (Otieno et al, 2009).

Model 1 is the pre-structural break at time *t* and model 2 applies post-structural break.

The Chow test main hypothesis is that the parameters of both models are set equal. Hence, if $\beta_1 = \delta_1$ and $\beta_0 = \delta_0$, then model 1 and model 2 can be expressed as a single regression line. As mentioned earlier, the chow test examines whether a single regression is more efficient than two separate regression lines.

The steps followed to detect the presence of a structural break as indicated by the Chow Test are:

1) Run a regression for the pooled data, pre- and post-structural break.
2) Run two separate regressions, pre- and post-structural break.
3) Calculate the F-test statistics from the following formula:

$$F - \frac{RSS_c - (RSS_1 + RSS_2)/k}{RSS_1 + RSS_2/n - 2k} \sim F\ (k, n - 2k) \qquad \text{(Eq.020)}$$

Where:

RSS_c : The residual sum of squared for the pooled sample.

RSS_1 : The residual sum of squared for the pre-structural break sample.

RSS_2 : The residual sum of squared for the post-structural break sample.

k*:* the number of regressors in each "unrestricted regressions"

n*:* the total number of observations.

4) Find the critical values in the F-test tables.
5) Accept or reject the null hypothesis, which is there is no structural break.

3.8 Conclusion

Chapter 3 began with stating the sources of data collection and defining the variables used, as well as providing the descriptive statistics of the selected variables. The correlation between the independent variables, U. K's commodity term of trade, weighted average Industrial Production Index, Real Effective Exchange rate, and GBP/EUR volatility was measured.

This chapter also provided a detailed theoretical explanation of the chosen models that will be used to determine the GBP/EUR exchange rate volatility, namely the EWMA, GARCH (1, 1), and EGARCH (1, 1) model and elaborated the main differences between each of the models adopted. It, also, provided the methodology used to determine our best fitted model using the three error statistics. Then, the purpose of introducing a dummy variable to our optimal model was explained to see whether Brexit had any impact on GBP/EUR volatility.

Additionally, this chapter explained the Autoregressive Distributed Lag (ARDL) model to be used in this thesis and presented its theoretical aspect. It also described the Chow test which aimed at detecting whether the Brexit vote has caused a structural break to the U. K's exports to Eurozone countries due to a volatile GBP/EUR exchange rate or not.

Subsequently, Chapter 4 presents the findings in order to check whether the Brexit vote has changed the pattern of the U. K's exports to Eurozone countries or not.

CHAPTER 4

FINDINGS

4.1 Introduction

In the previous chapter, we defined our selected variables, set their descriptive statistics, and conducted the normality test. Then, the adopted methodology was explained in detail. This chapter illustrates the obtained results under each of the selected volatility models: The EWMA, GARCH (1, 1), and the EGARCH (1, 1) models. The comparison to choose the optimal model is addressed using three error metrics, namely: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The model with the smaller error difference will be considered the most accurate. Subsequently, in the next part of this chapter, we will proceed by testing whether the Brexit referendum has changed the volatility structure of the GBP/EUR exchange rates while adding a dummy variable to our optimal model and testing its significance. Next, we will test the stationarity of our data and we will proceed by applying the autoregressive distributed lag (ARDL) approach to investigate the impact of GBP/EUR exchange rate volatility on UK exports to EU countries while addressing Brexit referendum and controlling for weighted average Industrial Production Index, real effective exchange rates, and commodity term of trade. Finally, the Chow test will be performed to detect whether Brexit referendum has caused any structural break to the U. K’s volume of exports to Eurozone.

4.2 Exchange Rate Volatility Measurement

One of the most fundamental topics evolves around the measurement of exchange rate volatility. Several empirical studies have utilized the moving average of the standard deviation of the logarithm of the exchange rate. This model was mainly criticist for its inability to capture the potential effects of high and low peak value of the exchange rates. Therefore, many models were developed to capture the properties of the exchange rate volatility, as previously explained in chapter 3..

The historical prices for GBP/EUR for the period spanning from January 1, 2010 until August 31, 2020 are used to compute the daily returns as per Equation 01. Then, the daily conditional variance is calculated from Equations 03, 06, and 11 for EWMA, GARCH (1,1) and EGARCH models, respectively. Each of the selected models' parameters are obtained by maximizing the Likelihood Function subject to the constraints specific for each model. The maximum likelihood function is a statistical technique that estimates the model parameters' by fitting the model to the sample's data. It includes selecting values for the parameters that increases the chance of the data occurring.

In practice, it is optimal to work with the logarithm of the likelihood function, which is expressed as:

$$\Lambda(\theta) = Log\, ⨍Y_T \ldots Y_1(\theta) = \sum_{i=1}^{T} Log\, ⨍Y_i \;|Y_{i-1} \ldots, Y_1(\theta_i)$$

Where:

θ = The value of the parameter for which the sample is most likely to observe.

$Log\, ⨍Y_T \ldots Y_1$ = The log of the joint density function of the time series.

By fitting the parameters obtained for each model, daily conditional variance is calculated. Results are then annualized using 250 trading years and the annual volatility is calculated as the square root of the annual conditional variance.

4.2.1 EWMA Model Parameters

As explained in the previous chapter, EWMA's parameter Lambda which is also known as the smoothing factor is estimated using Excel. After calculating the daily returns of GBP/EUR exchange rates as per Equation 01, the conditional variance is calculated as per Equation 03. The log Likelihood function is maximized using Excel solver to obtain the EWMA's parameter, Lambda.

Setting$0 \leq \lambda \leq 1$, the Log Likelihood and Lambda are presented in Table 3.

EWMA Model	
Parameter	**Coefficient**
Log Likelihood	26663.56
Lambda (λ)	0.9534

Table 3. The Log Likelihood and EWMA Model's Parameter.

Lambda (λ), as explained in the previous chapter, is the smoothing parameter or the decay factor that takes a value between 0 and 1. Results in table 3 show that EWMA model is stable for GBP/EUR exchange rates, since a value closer to 1 suggests a stable volatility parameter.

Figure 1 shows the variation of GBP/EUR exchange rate volatility under EWMA model as compared to the realized volatility.

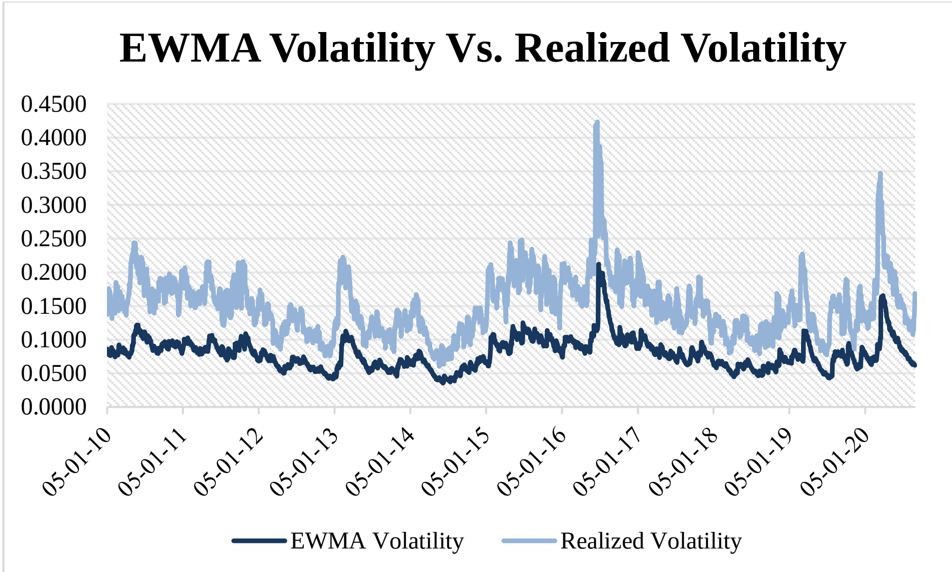

Figure 4. GBP/EUR Exchange rate volatility under EWMA Model.

4.2.2 GARCH (1, 1) Model Parameters

After calculating the daily returns of GBP/EUR exchange rates, the conditional variance is calculated as per Equation 06. Maximizing the Log Likelihood using EVIEWS is used to attain the appropriate GARCH (1, 1) parameters ($\omega, \alpha,$ and β). Same as the EWMA model, after estimating the parameters, GARCH (1, 1) volatility is calculated by taking the Square root of the conditional variance multiplied by 250. GARCH (1,1) parameters values and the loglikelihood results are shown in Table 4.

GARCH (1, 1) Model		
Parameters	**Coefficients**	**P-Values**
Log Likelihood	10799.60	-
Omega (ω)	0.000000509	0.000
Alpha (α)	0.06724	0.000
Beta (β)	0.91600	0.000

Table 4. Log Likelihood and GARCH (1, 1) Parameters.

The ARCH component (α), which determines the influence of market shocks on the volatility is 6.72%, which means that market shocks had a big effect on the volatility of the GBP/EUR. The GARCH component (β) known as the decay factor is 91.60% suggesting the relative importance of today's returns when determining the current variance rate. Noticeably, the "ω" term is close to zero. It is important to note that the sum of ARCH and GARCH components is 0.9832 (less than 1), ensuring a stable model and rapid decay towards the mean.

Figure 6 show the variation of GBP/EUR exchange rate volatility under GARCH (1, 1) model as compared to its realized volatility.

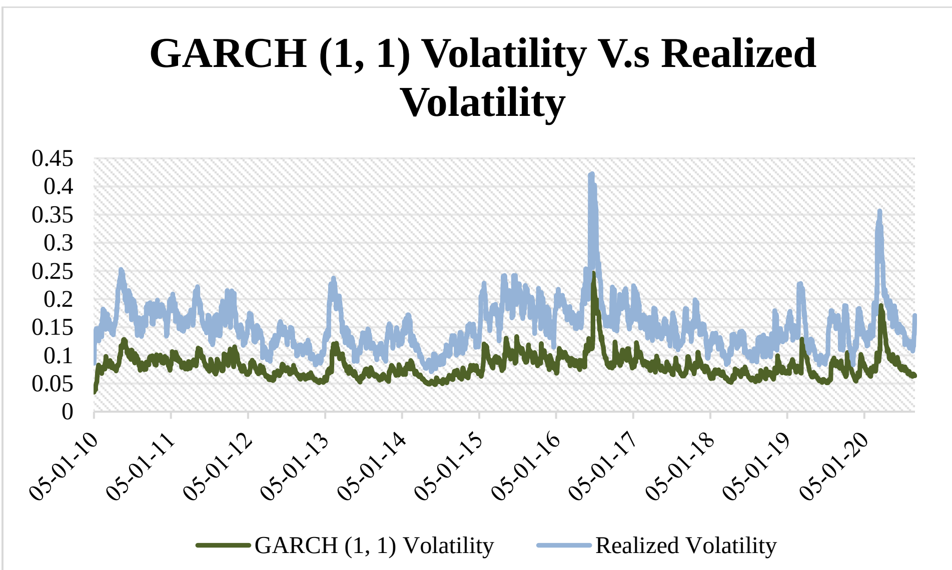

Figure 5. GBP/EUR Exchange rate volatility under GARCH (1, 1) Model.

4.2.3 EGARCH (1, 1) Parameters

Like the previous two models, estimating EGARCH (1, 1) model parameters starts by calculating the GBP/EUR daily returns. The log conditional variance is first calculated using Equation 11. The conditional variance is calculated as the exponential of the log conditional variance. Afterwards, we maximize the log likelihood function using EVIEWS to obtain the appropriate values of the

EGARCH (1, 1) parameters. Finally, GBP/EUR volatility is calculated as the square root of the conditional variance and multiply it by 250.

As mentioned before, EGARCH (1, 1) is distinguished from the GARCH (1, 1) by incorporating the impact of asymmetries on volatility and allowing the variance to react differently depending on the sign and size of the shock. Similarly, the ARCH term "α" represents the extent to which shocks affects future volatility in the returns. The GARCH term "β" represents persistence of past volatility. The most important coefficient is the leverage coefficient (γ), which describes how the sign of shocks affects volatility. The leverage coefficient in Table 5 is -2.828% and carries a negative value, meaning that negative shocks have a higher influence than positive shocks.

The ARCH term, "α", is positive indicating a relationship between past variance and current variance. The GARCH term, "β", is significantly high (97.44%), revealing a persistence in volatility.

EGARCH (1, 1) Model		
Parameters	**Coefficients**	**P-Values**
Log Likelihood	6889.58	-
Omega (ω)	-0.38471	0.000
Alpha (α)	0.15012	0.000
Gamma (γ)	-0.02828	0.000
Beta (β)	0.97446	0.000

Table 5. EGARCH (1, 1) Log Likelihood and Parameters.

Figure 8 shows the variation of GBP/EUR exchange rate volatility under EGARCH (1, 1) model as compared to the realized volatility.

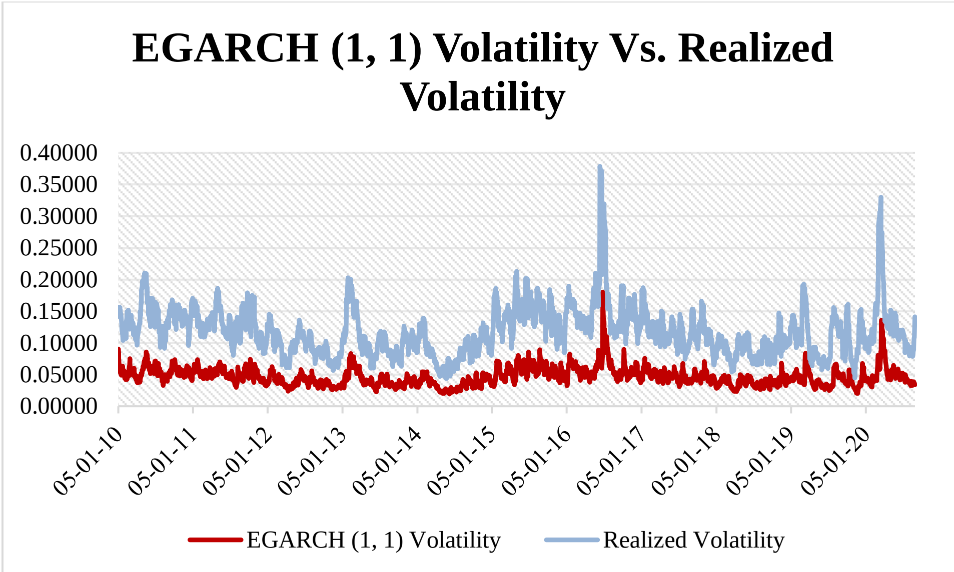

Figure 6. GBP/EUR Exchange rate volatility under EGARCH (1, 1) Model.

Figure 9 displays the GBP/EUR volatility under the three used approaches: EWMA, GARCH (1, 1), and EGARCH (1, 1) models in comparison with the realized volatility. As seen, the GARCH (1, 1) has generated more volatility on the time of the shock (Brexit referendum) and more convergence to the realized volatility than the remaining approaches.

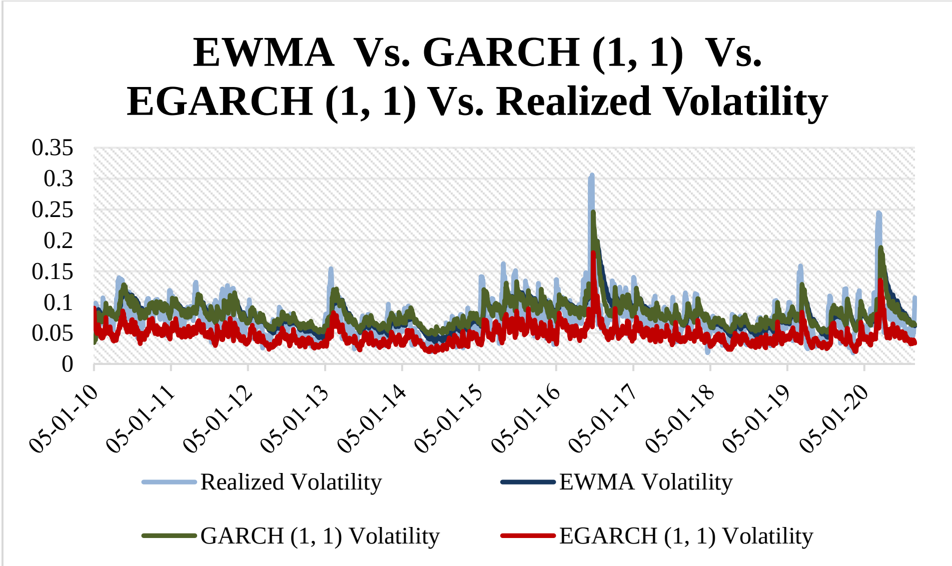

Figure 7. Comparison between EWMA, GARCH (1, 1), EGARCH (1, 1), and the realized volatility.

4.2.4. Optimal Model

The best-fitted model is selected based on the three-error metrics: The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These error metrics determine the best model by subtracting the calculated volatility for each model from the realized volatility. The model that obtains the least errors will therefore be ranked first, as previously explained in Chapter 3.

GBP/EUR Exchange rates: Optimal Model

Models	**RMSE**	**Rank**	**MAE**	**Rank**	**MAPE**	**Rank**
EWMA	0.030731	2	0.022649	1	36.301547	2
GARCH (1, 1)	0.030548	1	0.022848	2	37.703237	3
EGARCH (1, 1)	0.038319	3	0.028337	3	34.536369	1

Table 6. The RMSE, MAE, and MAPE ranking results.

Based on the three-error metrics, the results obtained doesn't show any superiority of one model over another since the differences are not significant. Therefore, we will proceed using the

GARCH (1, 1) model as our optimal model. As it is observed in figure 9, the GARCH (1, 1) graph is shown to be the most analogical to the realized volatility comparing to the EWMA and EGARCH (1, 1) models.

4.3. Change in Volatility Structure

After determining the optimal model between the three selected approaches, we move to address the second question concerning whether the Brexit referendum has changed the volatility structure of the GBP/EUR exchange rates. Our methodology consists of adding a dummy variable (D) to the GARCH (1, 1) model for the date after Brexit referendum. More specifically, this dummy is equal to 0 for pre-Brexit referendum period (Jan 1, 2010 until June 23, 2016) and 1 for post-Brexit referendum (24 June 2016 until August 31, 2020). Then we estimate the GARCH (1, 1) model while adding the dummy variable to the variance equation. It is represented as follows:

$$\sigma_t^2 = \omega + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \phi D_t$$

GARCH (1, 1) model parameters (ω, α, and β) have the same constraints and interpretations as explained earlier. The new parameter ϕ has no constraints as we are mainly interested in its sign and its significance. A positive sign of ϕ parameter signals that the volatility has increased post-Brexit referendum period, whereas a negative sign of ϕ suggests that the volatility has decreased post-Brexit referendum period. It is important that the ϕ parameter is statistically significant, otherwise the dummy variable is uncapable to deliver robust result. Thus, the dummy variable is supposed to provide information on the change in the volatility of the exchange rate through its sign and mainly through its significance. The results obtained are presented in Table 7.

GARCH (1, 1) with a dummy variable		
Parameters	**Coefficients**	**P-values**
Log Likelihood	6890.238	-
Omega (ω)	4.95E-07	0.0001
Alpha (α)	0.067254	0.0000
Beta (β)	0.916144	0.0000
Phi (ϕ)	2.74E-08	0.7113

Table 7. GARCH (1, 1) with a dummy variable log likelihood and parameters.

According to the results in Table 7. the dummy variable, which is represented by the parameter Phi (ϕ) does not show any significant effect. Although it is positive, the coefficient is very small and close to zero. Besides, its p-value is high, indicating a non-significant coefficient. Moreover, the other parameters of GARCH (1,1) model kept the same values as the one in the GARCH model without the dummy variable. Thus, it is not possible to conclude that the GBP/EUR volatility changed after the Brexit referendum.

4.4 Impact of Exchange rate Volatility on UK Exports

As mentioned before, this part will investigate the impact of exchange rate volatility on UK exports to Eurozone countries namely, Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherland, Portugal, Slovakia, Slovenia, and Spain, mainly using monthly data from January 2010 to August 2020, and the Autoregressive Distributed Lag (ARDL) method of Pesaran et al. (2001) based on the following equation:

$$\Delta LEX_j^k = \alpha_0 + \lambda_1 LEX_{t-1} + \lambda_2 LIPI_{t-1} + \lambda_3 LREER_{t-1} + \lambda_3 LTOT_{t-1} + \lambda_4 LVOL_{t-1} + \sum_{i=1}^{l_1-1} \theta_{1i}\, \Delta LIPI_{t-i}^k + \sum_{i=1}^{l_2-1} \theta_{2i}\, \Delta LREER_{t-i} + \sum_{i=1}^{l_3-1} \theta_{3i}\, \Delta LTOT_{t-i} + \sum_{i=1}^{l_4-1} \theta_{4i}\, \Delta LVOL_{t-i} + \varepsilon_{it}$$

Where:

LEX is the natural logarithm of U. K's real exports to eurozone countries,

LIPI is the natural logarithm of Eurozone weighted average Industrial Production Index,

LREER is the natural logarithm of the Real effective exchange rates,

LTOT is the natural logarithm of Commodity Term of Trade,

LVOL represents the natural logarithm of GBP/EUR exchange rate volatility estimated using GARCH (1,1).

$\theta_{1i}, \theta_{2i,} \theta_{3i,} \theta_{4i}$ are the short-run coefficients of the four independent variables (LIPI, LREER, LTOT, and LVOL),

$\lambda_1, \lambda_{2,} \lambda_{3,} \lambda_4$ are the long-run coefficients of the four independent variables (LIPI, LREER, LTOT, and LVOL) and

ε_{it} is the disturbance term.

This method showed superior performance as compared to other techniques (Iqbal and Uddin, 2013). Prior to constructing our models, some tests are needed.

4.4.1 ARDL Unit Root Test

Before examining the existence of a long run relationship (co-integration) between the variables, and as a starting point, we must analyze the order of integration of the variables considered. The ARDL method can be applied on a time series data, irrespective of whether these variables are I(0) or I(1) and can provide unbiased estimates of the long run model. However, it is necessary to check that none of variables are I(2), otherwise, ARDL would produce spurious results. The Phillips-Perron (PP) test (Phillips and Perron, 1988) is performed to test the stationarity of our variables and their order of integration using a drift term and both with and without trend. The PP test's null hypothesis states that the series has a unit root (non-stationary). The null hypothesis of no-stationarity is rejected if the $|t - statistics|$ value is greater than the $|\text{critical values}|$ or when their p-values are less than the significance level. The Lag-lengths for PP independent variables are chosen using the Newey-West Bandwidth.

Phillips-Perron Unit Root Test

Variables	**Levels**				**First Difference**			
	Constant	**P-Value**	**Constant & Trend**	**P-Value**	**Constant**	**P-Value**	**Constant & Trend**	**P-Value**
LEX	-5.6035***	0.0000	-6.3903***	0.0000	-18.9794***	0.0000	-17.5736	0.0000
LIPI	-2.2924	0.1760	-2.1592	0.5077	-11.6446***	0.0000	-13.5737	0.0000
LREER	-1.792541	0.3828	-1.8566	0.6710	-12.0900***	0.0000	-12.0617	0.0000
LTOT	-2.0815	0.2525	-2.4570	0.3489	-12.2175***	0.0000	-12.0883	0.0000
LVOL	-5.4769***	0.0000	-5.4048***	0.0001	-12.9999***	0.0000	-12.9487	0.0000

Table 8. Phillips-Perron Unit Root Tests.

Note: *, **, and *** are respectively significant at 10%, 5%, and 1%.

Table 8 shows that all variables are either I(0) and I(1) and none of them are I(2). More specifically, LVOL and LEX are I(0) since the p-value is less than 0.01 and the remaining variables (LIPI, LREER, and LTOT) are I (1) since the p-value is also less than 0.01. In other words, unit root tests show the variables are a mixture of I(0) and I(1). These outcomes satisfy the condition for testing and using ARDL. Hence, the ARDL approach is suitable to test the relationship in level variables.

4.4.2 ARDL Optimal Lag Length

After establishing that all the variables are either I (0) or I (1), and not I (2), the second step is to determine the lag order of the ARDL using the appropriate lag selection criteria consisting of the Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan-Quinn Information criterion (HQ) which are basically considered when ARDL estimating technique is employed (Raza et al., 2015). Using EVIEWS 10, we run the normal unrestricted VAR to determine the optimal lag length of our dependent variable. As per FPE, AIC, SC, and HQ, our optimal lag length for exports is five. Table 9 illustrates our obtained results.

Lag Length Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	82.17534	NA	0.015134	-1.352922	-1.329693	-1.343489
1	116.0927	66.70422	0.008744	-1.901546	-1.855088	-1.882679
2	122.108	11.72979	0.008043	-1.985134	-1.915446	-1.956833
3	122.2122	0.201319	0.008164	-1.970203	-1.877286	-1.932469
4	131.6073	18.00734	0.007098	-2.110121	-1.993976	-2.062954
5	134.4918	5.480557*	0.006879*	-2.141530*	-2.002155*	-2.084929*
6	134.5006	0.016677	0.006994	-2.125011	-1.962407	-2.058977
7	134.661	0.299342	0.007093	-2.111017	-1.925184	-2.035549
8	134.9609	0.554781	0.007177	-2.099348	-1.890286	-2.014447

Table 9. Var Lag Order Selection Criteria.

*indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error
AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion

4.4.3 Strength of the Model Selection Criteria

This research uses the criteria graph approach as shown in figure 10, to identify the top 20 models and determine the best fitted model to our series using the Akaike Information Criterion (AIC) which was found to be superior as compared to SIC and HQ for selection of the model (Rotimi et al, 2019). The decision rule for this approach is that the lower the AIC, the better the model, thus, the best ARDL model is the one with the lowest value of AIC. Figure 10 shows that ARDL (5, 4, 0, 1, 0) is the best model as it has the minimum negative value of AIC among 20402 simulated models. In other words, the best model has a lag of 5 for Exports (LEX), a lag of 4 for Eurozone weighted average IPI (LIPI), 0 lag for Real effective Exchange rate (LREER), a lag of 1 for Term of Trade (LTOT), and finally a lag of 0 for GBPEUR exchange rate volatility (LVOL).

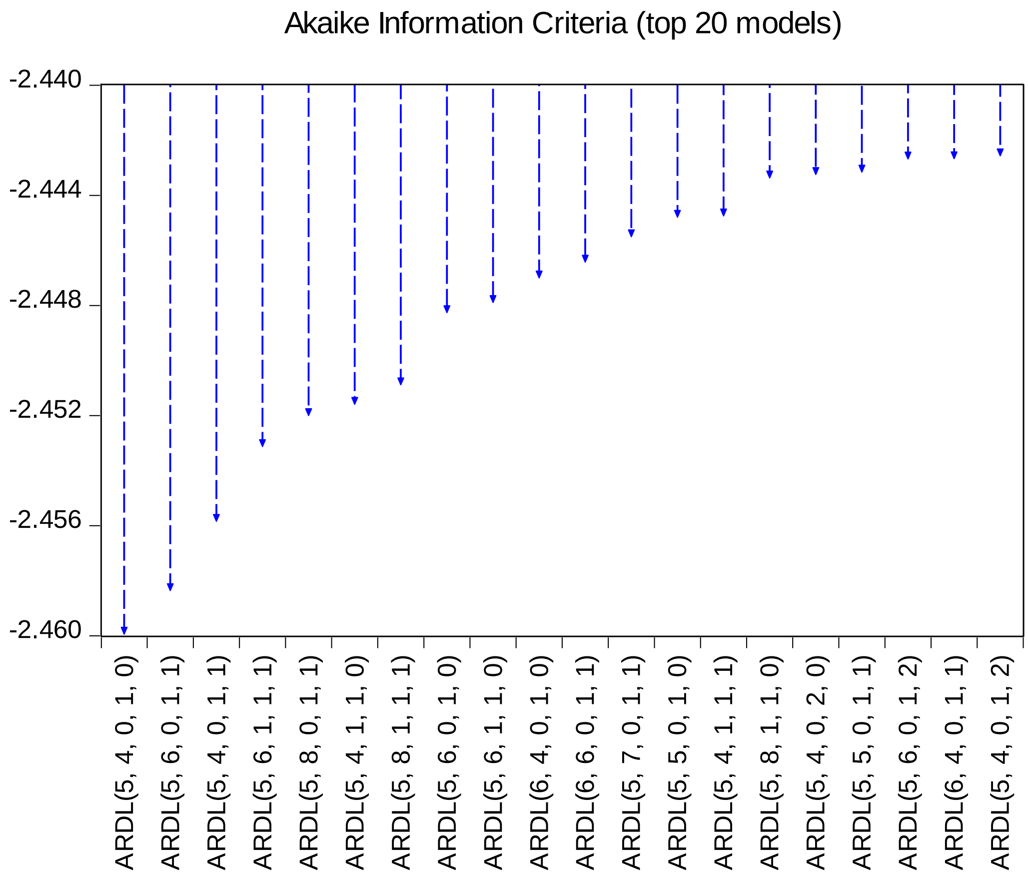

Figure 8. Akaike Info Criterion (Top 20).

Appendix A shows the Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information criterion (HQ) of many models.

4.4.4 Normality Test, Serial Correlation Test (LM Test), and Heteroskedasticity Test

After finding the order of the ARDL model, errors should be tested for normality, serial correlation, and heteroskedasticity. We use the Jarque-Bera, Lagrange Multiplier (LM), and Breusch-Pagan-Godfrey tests to inspect the reliability of our model using EVIEWS 10. First, we test the normality of the residuals using the Jarque-Bera test. Under the null hypothesis of a normal distribution, the reported probability is the probability at which the Jarque-Bera statistic exceeds the observed value. Thus, the null hypothesis is rejected if the p-value is lower than the significance level. The results shown in Table 10 indicate the normality of our residuals since the p-value (0.5433) is greater than the significance level (1%, 5% and 10%).

Normality Test for Residuals: Jarque – Bera Test

Jarque-Bera Value	**Probability**
1.220171	0.543304

Table 10. The Jarque-Bera Normality Test.

Second, we run the Breusch-Godfrey Serial Correlation LM test to determine whether we accept or reject the null hypothesis of no serial correlation in errors. If the probability of F is greater than the significance level, then we do not reject the null hypothesis. To proceed with the bound testing, it is vital for errors to be serially independent. The results shown in Table 11 indicate that errors are not serially correlated since the p-value of 0.5373 is greater than 1%, 5%, and 10% significance level.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.878675	Prob. F (8, 37)	0.5373
Obs*R-squared	8.154493	Prob. Chi-Square (8)	0.4185

Table 11. The Breusch-Godfrey Serial Correlation LM Test.

We proceed with the Breusch-Pagan-Godfrey test to detect whether our model has heteroskedasticity problems, with a null hypothesis of homoskedasticity of errors (no heteroskedasticity). If the probability of F is greater than the significance level (1%, 5%, or 10%) we fail to reject the null hypothesis. As per Table 12, we do not reject the null hypothesis since p-value is equal to 0.6455, hence errors are homoscedastic.

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.827376	Prob. F (24,45)	0.6455
Obs*R-squared	12.78370	Prob. Chi Square (24)	0.6190
Scaled explained SS	7.336613	Prob. Chi-Square (24)	0.9476

Table 12. Breusch-Pagan-Godfrey Heteroskedasticity Test.

4.4.5 CUSUM and CUSUM of Squares Stability Test

The stability of long-run coefficients along with short-run dynamics are estimated by running the CUSUM and CUSUM of Squares stability test. The CUSUM test uses the cumulative sum of recursive residuals, whereas the CUSUMSQ test is based on the cumulative sum of the squared recursive residuals (Thi Thuy, 2019). As per Figure 11 and Figure 12 the CUSUM and CUSUMSW statistics are within the critical boundaries. Hence, there is no structural instability in our model.

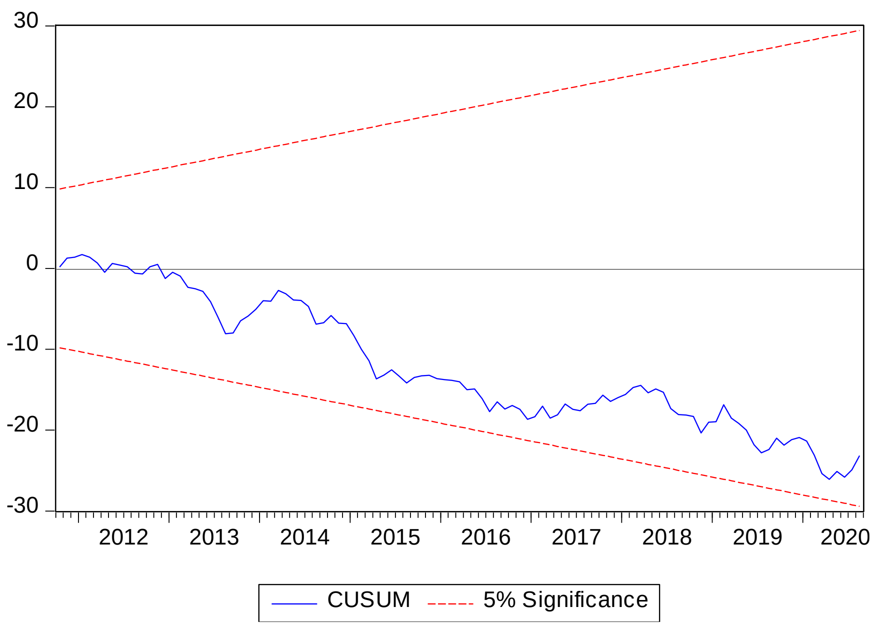

Figure 9. The CUSUM Test.

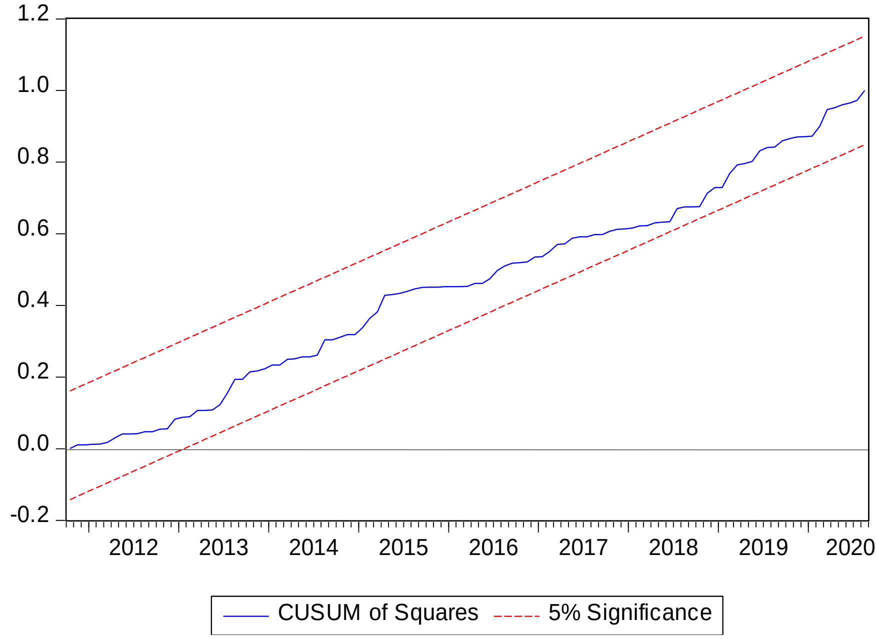

Figure 10. The CUSUMSQ Test.

4.4.6 Bound Testing for Level Relationship

The next step is to test for the existence of long run relationship between Exports and other regressors. The test is called the “bound testing” approach to cointegration and it is associated with the hypothesis testing that all long-run parameters are equal to each other (i.e., long run relationship does not exist), against the alternative that the long-run relationship exists. Thus, the hypothesis is tested using F-statistic. A F-statistic value greater than the upper bound indicates the existence of a long-run relationship, while a F-statistic value less than the lower bound indicates no long-run relationship. If F-statistic value is between the upper and lower bounds, then the long-run relationship is inconclusive. As per Table 13, the F-statistics value (3.802021) exceeds the upper bound of 3.698 at 5% significance level, supporting the presence of a long-term relationship between exports, industrial production index, real effective exchange rate, commodity term of trade, and exchange rate volatility in the export equation.

It is worth mentioning that we repeated the analysis by including a dummy variable D that takes the value 1 from June 2016 until August 2020, 0 otherwise. However, results did not change.

F-Bounds Test	**Null Hypothesis: No levels relationship**			
Test Statistic	**Value**	**Sig.**	**I (0)**	**I (1)**
			Finite Sample: n=80	
F-statistic	3.802021	10.00%	2.303	3.220
k	4	5.00%	2.688	3.698
		1.00%	3.602	4.787

Table 13. The Bounds Test.

4.4.7 Long Run Relationship

Since the results of the Bound testing indicated the presence of a long-run relationship, we proceed by looking at the long-run coefficients. Table 14 shows that all of variables could significantly explain the variation in exports. TOT is significant at 10%, whereas IPI, REER and VOL are significant at 5%.

Long-run Coefficients Estimates of Linear ARDL Model				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LIPI	0.8723	0.3402	2.5640	0.0117**
LREER	-0.5347	0.2566	-2.0838	0.0396**
LTOT	2.2448	1.2952	1.7333	0.0859*
LVOL	-0.2458	0.1157	-2.1240	0.0360**
@TREND	-0.0019	0.000485	-3.9364	0.0001***

EC = LOG(EX) - (0.8723*LIPI -0.5346*LREER + 2.2448*LTOT -0.2458*LVOL -0.0019*@TREND)

Note: *, **, and *** are significant of 10%, 5%, and 1% respectively

Table 14. The Long-run Relationship.

The results indicates that the impact of IPI on volume of exports is positive and significant, which suggests that an increase in industrial production index will increase U.K's volume of exports to Eurozone countries in the long run. The positive effect of IPI implies that an increase in the trading partners' income will increase the exports of UK. The finding is consistent with the results of previous studies showing that a higher income level on the export destination country may encourage larger exports.

Meanwhile, surprisingly, the commodity term of trade has a positive impact on the volume of exports, significant at 10%, suggesting that an increase in the exports price index relative to the imports price index will increase the volume of exports in the long run. An improvement in the commodity term of trade should stimulate investments in exportation of commodities, hence economic growth, due to the higher relative export prices (Dabus, et al., 2019).

As expected, the real effective exchange rate coefficient is negative and statistically significant at 5%, implying that if the real exchange rate increases, the export volume will decrease. Therefore, an appreciation in the value of pound relative to other currencies will make exports more expensive, resulting in a loss in the trade competitiveness and hindering export performance.

Finally, the exchange rate volatility has proven to be negative and statistically significant at 5%, suggesting that an increase in exchange rate volatility reduces the volume of export. This is in line with theoretical models of the behavior of risk-averse exports, since the higher the volatility, the higher the uncertainty and risks. Under scenarios of high volatility, risk-averse traders may lower trading across borders as they could incur unexpected costs associated with exchange rates volatility (Doganlar, 2002).

4.4.8 ARDL- ECM model

As a next step, we proceed by examining both the long-run and short-run association amidst the exchange rate volatility and U.K exports to Eurozone using the Error Correction Model (ECM) approach. Thus, following Pesaran (2001), the study introduced the ECM coefficient using the long-run normalized estimates to determine the speed of adjustments at which the model returns to its equilibrium. In general, ECM should be negative and statistically significant to indicate that the parameters cointegrate and that there is a long-run adjustment. Table 15 provides the summary of the error correction representation and the results fulfill the above conditions. ECM has the correct sign (negative coefficient of -0.4745) and is statistically significant at 1% confidence level. The minus sign indicates the presence of disequilibrium in earlier short-run period and a further evidence of cointegration among the variables in the model and the coefficient of 0.4745 indicates that the speed of adjustment is at the rate of 47.45%, suggesting that 47.45% of the deviation from the long-run equilibrium period between variables is periodically corrected.

For a compact and more efficient way of reporting results, only significant results are displayed. The results of the short-run dynamic coefficients show that LIPI, LTOT, and LVOL are significant, displaying an impact on U. K's exports to Eurozone Countries. Interestingly, the coefficient of LVOL is negative and significant in the short run as well, indicating that if exchange rate volatility increases, export volume will decrease in the short run. Results support Arize and Malindretos (1998) who argued that higher exchange rate volatility will depress export volume because of an increase in adjustment costs due to higher uncertainty and risks. Another possible explanation, as reported by Kalaivani et al. (2012), is that the volume of export is reduced due to the lack of hedging opportunities which causes risk-averse firms to reduce their exports in the face of high uncertainty.

The short-run coefficient of IPI variable is positive and significant at *t-3*, suggesting that real trading partners' income exerts a positive impact on exports of UK for the short-run, as well as for the long-run.

Surprisingly, the short-run and long-run coefficient of commodity TOT is positive and highly significant. Increase in the demand for U.K's commodities is reflected in the increase of exports prices.

Finally, an increase in REER does not show any significance for the short-run, suggesting that an appreciation in the local currency impacts exports only in the long-run.

Short-run Coefficients Estimates of ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ΔLEX*(t-4)*	0.3257	0.0863	3.7725	0.0003***
ΔLIPI*(t-3)*	0.6458	0.3037	2.1266	0.0357**
ΔLTOT	6.0892	1.2545	4.8539	0.0000*
ΔLVOL	-0.2180	0.0938	-2.3243	0.0219**
ECM *(-1)*	-0.4745	0.1095	-4.3348	0.0000*

Prob(F-statistic)	0	**CUSUM**	Stable
Adjusted R-squared	0.543194	**CUSUMSQ**	Stable

Table 15. The Short-run Coefficients Estimates.

Note: *, **, and *** are significant of 10%, 5%, and 1% respectively.

Once the ECM model has been estimated, the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMQ) test are applied to assess parameter stability (Pesaran and Pesaran, 1997). The results indicate the absence of any instability because the plots of CUSUM and CUSUMQ statistic fall inside the critical bands of the 5% confidence interval.

Furthermore, other diagnostics tests are performed again, mainly serial correlation (LM), heteroskedasticity, and normality test to insure the stability of the long-run coefficients. Results shown in Table 16 do not indicate any problem of serial correlation, heteroskedasticity and non-normality of the residuals since their p-values are 0.4240, 0.8671, and 0.5170 respectively. Thus, results provide satisfactory outcomes.

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.022614	Prob. F (8,92)	0.4240
Obs*R-squared	9.132724	Prob. Chi-Square (8)	0.3312
Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.563401	Prob. F (19,100)	0.8671
Obs*R-squared	7.122075	Prob. Chi-Square (19)	0.8494
Scaled explained SS	4.374252	Prob. Chi-Square (19)	0.9757
Normality Test: Jarque-Bera			
Jarque-Bera	1.319117	Prob.	0.517079

Table 16. Diagnostic Tests.

4.5 The Chow Test

To answer our last research question, whether the Brexit referendum has caused a structural break in the relationship between U. K’s exports to Eurozone countries and GBP/EUR exchange rate volatility or not, we employ the Chow test using EVIEWS 10. The latter permits us to discover whether at a particular date a structural break occurred in the regression coefficients. The null hypothesis is the non-existence of structural break. The chow breakpoint test compares the sum of squared residuals attained by fitting both time sets (Pre and Post Brexit) with the sum of squared residuals obtained when distinct equations are performed. If the calculated Chow F-statistics is greater that the critical value of the F-distribution, we may reject the null hypothesis.

First, we identified possible break dates by using the Bai–Perron test. The estimated break dates suggested by the Bai–Perron tests in Table 17 are Month 4 and 10, 2012, and Month 7, 2018. The first breakpoints are pre-Brexit, so they will be disregarded. The second break point (July 2018) might be related to the uncertainty associated with negotiations between the European Union and United Kingdom to agree on Brexit treaty. The year 2018 is considered as the "Year of Brexit decisions" as state by Barbara Wesel (2018), where the exit treaty and U.K- EU future negotiation are being exchanged. The Bai-Perron sequential test does not reject the null hypothesis of l =1 and l =2 at 5% significance level, which means we only have 2 breakpoints.

Multiple breakpoint tests			
Bai-Perron tests of L+1 vs. L sequentially determined breaks			
Sequential F-statistic determined breaks:		2	
Break Test	**F-statistics**	**Scaled F-Statistics**	**Critical Value**
0 vs. 1 *	2.87217	31.59387	27.03
1 vs. 2 *	3.56221	39.18431	29.24
2 vs. 3	1.75361	19.28971	30.45

* Significant at 0.05 level.

Break Dates:

	Sequential	**Repartition**
1	2012M10	2012M04
2	2018M07	2018M07

Table 17. The Bai-Perron Multiple Breakpoint Test.

Thus, we proceed by employing the Chow test on two dates: June 2016 (Brexit referendum date) and July 2018 (post-Brexit referendum). The Chow breakpoint test has a null hypothesis of no breaks at specified breakpoints. If F-statistics probability is greater than the significance level, we fail to reject the null hypothesis of no breaks at specified breakpoint. If the F-statistics is statistically significant (p-value is less 1%, 5%, or 10%), then we reject the null hypothesis. According to the results in Table 18, we do not reject the null hypothesis which elucidates no structural break in June 2016 since prob. F (k, n-k-1) is greater than 1%, 5%, and 10%, where "k" is the number of regressors and "n" is the number of observations. However, Table 19 shows that the null hypothesis is rejected at 5% confidence level, indicating a structural break post the announcement of Brexit and during the transition period.

Chow Breakpoint Test: 2016M06 No breaks at specified breakpoint			
F-statistic	1.079528	Prob. F(11,101)	0.3852
Log likelihood ratio	13.67253	Prob. Chi-Square(11)	0.2516
Wald Statistic	11.87481	Prob. Chi-Square(11)	0.3731

Table 18. The Chow Breakpoint Test- June 2016.

Chow Breakpoint Test: 2018M07 No breaks at specified breakpoint.			
F-statistic	2.202398	Prob. F (11,101)	0.0198
Log likelihood ratio	26.44533	Prob. Chi-Square (11)	0.0056
Wald Statistic	24.22638	Prob. Chi-Square (11)	0.0118

Table 19. The Chow Breakpoint Test- July 2018.

4.6 Conclusion

This chapter was mainly divided into three main parts. Each part has answered one of this research's main research questions. First, we detected the optimal model between three different approaches (EWMA, GARCH (1, 1), and EGARCH (1, 1)) based on the three-error statistics (RSME, MAE, and MAPE). It is proved that the GARCH (1, 1) is the optimal model for our GBP/EUR exchange rate series. Based on this selection, we proceed to answer the second research question, and determine whether the Brexit referendum have caused a structural break in the GBP/EUR exchange rate volatility or not. We added a dummy variable to GARCH (1, 1) model, that enabled us to conclude that no structural break in the GBP/EUR exchange rate volatility has occurred post-Brexit referendum.

Next, we proceeded to examine the impact of exchange rate volatility on U.K's exports to Eurozone countries by employing the Autoregressive Distributed Lag (ARDL) model. Based on multiple studies performed, this approach has proven its ability to provide unbiased results irrespective of the level of integration of the variables. Therefore, we performed the Phillips-Perron unit root test to detect the level of integration of our variables. It was shown that two of our regressors (LEX and LVOL) are stationary at I(0) while the others are stationary at I(1). Based on the ARDL bound test, it was shown that there is a cointegration relationship between U.K's volume of exports to eurozone countries, weighted average industrial production index, real effective exchange rates, commodity term of trade, and GBP/EUR exchange rates. All selected variables have a long-run impact on the volume of exports. More specifically, U.K's exports to eurozone countries will be negatively impacted by the real effective exchange rates (LREER) in the long-run but not in the short-run. Thus, a depreciation in the pound against other currencies will stimulate U.K's exports to Eurozone countries in the long run. One unanticipated finding is that the commodity term of trade (LTOT) has a positive impact on U.K's volume of exports to Eurozone in both the long-run and short-run. Indicating, an improvement in commodity terms of trade promotes traders to export more, due to an increase in exports prices, hence production is more profitable. Moreover, the weighted average industrial production index (LIPI) positively affect the U.K's volume of exports to Eurozone countries in the short-run and long-run. This implies that any improvement in the economic activity of UK's trading partners' will increase the volume of U.K's exports to Eurozone countries. On the other hand, the GBP/EUR exchange rate volatility (LVOL) has a negative impact in the short-run and long-run. A higher exchange rate volatility depresses the volume of exports, and as explained earlier this can be due to the lack of hedging opportunities and the risk averse nature of trading agents. On another note, the speed of adjustment in modifying the deviation and in returning the long-run equilibrium after a shock in the time series is about 47.45 %. As a conclusion, the higher the uncertainty reflected in the exchange rate volatility, caused by Brexit referendum and Brexit news, caused negative outcomes in the form of a reduction of U.K's exports to Eurozone countries.

Finally, the last part of this chapter tackled the presence of a structural break in the relationship between U.K's volume of exports to Eurozone and exchange rate volatility post-Brexit referendum while employing the Chow-test. It was detected a structural break in July 2018. This might be related to the uncertainty associated with the ongoing negotiations between the European Union and United Kingdom to agree on Brexit treaty.

Chapter 5 will subsequently present a more detailed analysis of our findings in chapter 4, link it to previous studies and provide some recommendations as well as the limitations of this research.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

The EU membership has given many advantages, most notably the free movements of goods and services. This feature has a significant contribution to the economic growth of a country. In the case of the United Kingdom, and since U.K is one of the largest trading partners with the EU, leaving the Union would impact exports, either positively or negatively, depending on the withdrawal agreement that will be reached between the two economic areas. Moreover, the Brexit referendum has caused an instant shock to the financial market and has depreciated the pound's value to a level that had not been observed before. This depreciation is linked to the ambiguity of the future relationship between both parties. As stated by Scivoletto (2019), multiple economic experts assert that the increased uncertainty is accountable for the volatility of the British pound; however, there is no empirical evidence for this proclamation. Therefore, the aims of this research are (i) to shed light on the best-fitted model to assess the GBP/EUR exchange rate volatility, (ii) to determine whether the Brexit referendum has changed the structure in the GBP/EUR exchange rate volatility, and (iii) to test whether a volatile exchange rate has a positive or negative impact on U. K's volume of exports to Eurozone countries, and finally (iv) to detect, using the Chow test, whether Brexit announcement has created a structural break in the relationship between exchange rate volatility and exports.

Therefore, this chapter concludes the overall study by presenting first the analysis of the main findings. Then, it will discuss the limitations of this research and finally suggests some recommendations for future research.

5.2 Analysis of the Main Findings

The first objective of this study consists of finding the best-fitted model to predict the volatility of the British pound relative to the Euro. Using daily data spanning from January 1st, 2010 to August 31st, 2020, the EWMA, GARCH (1, 1), and EGARCH (1, 1) approaches have been used to calculate the exchange rate volatility to find the optimal model that represents the GBP/EUR exchange rate volatility. The decay factor (lambda) obtained in EWMA suggests that a high variance will tend to be enduring for a longer time. The GARCH (1, 1) model shows volatility clustering in the GBP/EUR time series. Moreover, today's volatility is influenced by the previous period's volatility. This means that the Brexit referendum has an enduring effect over the next period's volatility. Finally, the EGARCH (1, 1), which takes into consideration the leverage effect in addition to the volatility clustering, reveals a significant and negative leverage effect, indicating that negative shocks, such as the Brexit referendum, denote a higher conditional variance in the next period than positive shock with the same magnitude (Abdallah, 2012). By looking at the three-errors metrics, the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE), none of the models outperformed the other model. Thus, we proceed by using the GARCH (1, 1) model since it was shown graphically to be the closest to the realized volatility. Our choice was supported by Abdallah's (2012) who proved that the GARCH models are the most adequate models to be utilized when modeling exchange rate volatility.

Subsequently and to tackle whether there was any change in the volatility structure pre-Brexit referendum and the post-Brexit referendum (second research question), we added a dummy variable, Phi (ϕ), to the optimal model, GARCH (1, 1). Nonetheless, this approach did not deliver any significant information, as the Phi (ϕ) parameter was not significant. Our results are consistent with Scivoletto (2019) who also studied the changes in the structure of exchange rate volatility of GBP/EUR after the announcement of the Brexit, by similarly adding a dummy variable to the GARCH (1, 1) model.

Next, this research examines the impact of the British pound relative to Euro exchange rate volatility on U.K's exports to Eurozone countries, namely Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherland, Portugal, Slovakia, Slovenia, and Spain (third research question). Using monthly data from January 2010 to August 2020, the Autoregressive Distributed Lag (ARDL) approach was employed. This approach's advantage is that it is suitable for small-size samples and mixed regressors of I(0) and I(1). The export regression consists of exchange rate volatility, which is calculated using the optimal model, GARCH (1, 1), as one of the independent variables together with three other variables, namely, the weighted average industrial production index, the commodity term of trade, and the real effective exchange rates. Our results support the existence of a cointegration relationship between the weighted average industrial production index, the real effective exchange rate, commodity term of trade, and the U.K's exports to Eurozone countries.

Regarding the relationship between exchange rate volatility and exports, our result confirms the presence of a negative relationship in the long-term and in the short-term. In other words, an appreciation in exchange rate volatility will depress the volume of exports. Thus, the arising uncertainty created as a result of the Brexit referendum has a negative impact on U.K's exports to Eurozone countries. Our results are consistent with Ramli, et al. (2012)'s study who found a significant negative impact of the exchange rate volatility of five ASEAN countries (Malaysia, Singapore, the Philippines, Indonesia, and Thailand) on their exports to the United States.

Furthermore, Industrial Production Index (IPI) positively impacts U.K exports to Eurozone countries in the short-run and in the long-run. This indicates that the trading partner's income exerts a positive impact on the volume of exports. Moreover, the commodity Term of Trade variable (TOT) has shown an unanticipated result with a positive impact in the short-run and long-run, as well, while the Real Effective Exchange Rate (REER) variable has shown a negative impact on U.K's exports to Eurozone in the long-term only. Thus, an increase in the value of the pound relative to other currencies will harm exports by making goods more expensive. As a conclusion, uncertainty related to no-deal agreements will increase the exchange rate volatility level which will depress exports.

Finally, to answer our last research question regarding whether the Brexit referendum has caused a structural break in the relationship between the U.K's exports to eurozone countries and the exchange rate volatility, we employ the Chow test. The Chow test enables us to detect whether, at a particular date due to a particular event, such as the Brexit referendum, a structural break has occurred in the regression coefficients. The Chow test detected a structural break in July 2018 which is linked to the increased uncertainty and negotiations of divorce agreement between the two parties. Consequently and although the Brexit referendum did not cause a structural break in the relationship between the GBP/EUR exchange rate volatility and U.K's exports to Eurozone countries, the uncertainty created with the ongoing negotiations and fearing a no-deal agreement between EU and U.K caused a structural break.

As a conclusion to this work, the so-called "Brexit" led to several doubts about the future relationship between the U.K and the EU which was translated directly with a sharp depreciation of the sterling pound (GBP). As previously demonstrated, our study detected a negative relationship between the GBP/EUR exchange rate volatility and exports. Consequently, a risk-averse firm with transactions denominated in GBP should hedge their receivables to reduce any losses resulted from the negative movement of the GBP and its volatility (Scivoletto, 2019).

5.3 Limitation of the Research

The first limitation is the absence of the Gross Domestic Product (GDP) monthly data. The GDP would have been a better proxy to reflect a country's economy's output and the size of its economy. Another limitation is using different types of GARCH models, such as the Threshold Autoregressive Conditional Heteroskedasticity (TGARCH), that can react differently to exchange rate volatility when experiencing good or bad news. The Asymmetric Power Autoregressive Conditional Heteroskedasticity (AP-ARCH) model could have also been used. This model type considers both the asymmetric and leverage effects by alternating the second order of the disturbance term into a more flexible exponent. The third limitation concerning the period chosen, a more extended period (more than 10 years) would have been more favorable when implementing the ARDL approach for a more robust outcome. An extended period may change the results generated.

5.4 Implications and recommendations

Although this research provides an analysis on GBP/EUR exchange rate volatility impact on the U.K's exports to Eurozone countries due to the announcement of Brexit, there is a need for future researches related to this subject. For example, it could be interesting to undertake similar research after the exit deal's actual announcement between the U.K and the EU. The volatility and structure of GBP/EUR may change or react differently. Another exciting research study is studying the volatility structure changes of GBP/EUR under different exit agreement scenarios (i.e., Hard

Brexit, Soft Brexit, and no-deal agreement). It can be possibly executed by introducing a dummy variable to the GARCH model under each scenario. Also, a similar study can be executed by testing the impact of Brexit on the U.K's export to each of its major trading partners separately. It can be done by including different variables and using other types of GARCH models when modeling exchange rate volatility, such as the Threshold Generalized Auto-Regressive Conditional Heteroskedasticity (TGARCH). This suggested research can implement the MZ test instead of the chow test when determining the presence of a structural break in the relationship between exchange rate volatility and the U.K's exports to each of its main trading partners in the Eurozone countries. The MZ test is a more sophisticated test than the Chow test since it considers changes in the error term variance and the changes in the regression coefficients simultaneously.

APPENDIX A.

Model Selection Criteria Table

Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
23319	162.358230	-2.459802	-2.086139	-2.308069	0.708147	ARDL(5, 4, 0, 1, 0)
21860	165.263741	-2.458214	-2.014489	-2.278031	0.713718	ARDL(5, 6, 0, 1, 1)
23318	163.114194	-2.455701	-2.058683	-2.294484	0.709006	ARDL(5, 4, 0, 1, 1)
21779	165.952860	-2.452989	-1.985910	-2.263323	0.714156	ARDL(5, 6, 1, 1, 1)
20402	166.885863	-2.451863	-1.961430	-2.252714	0.715732	ARDL(5, 8, 0, 1, 1)
23238	162.861579	-2.451455	-2.054437	-2.290239	0.707768	ARDL(5, 4, 1, 1, 0)
20321	167.819227	-2.450743	-1.936956	-2.242110	0.717272	ARDL(5, 8, 1, 1, 1)
21861	163.663054	-2.448119	-2.027747	-2.277419	0.708824	ARDL(5, 6, 0, 1, 0)
21780	164.641071	-2.447749	-2.004023	-2.267566	0.710706	ARDL(5, 6, 1, 1, 0)
16758	162.588409	-2.446864	-2.049846	-2.285648	0.706424	ARDL(6, 4, 0, 1, 0)
15299	165.553953	-2.446285	-1.979205	-2.256619	0.712233	ARDL(6, 6, 0, 1, 1)
21131	165.499158	-2.445364	-1.978284	-2.255698	0.711968	ARDL(5, 7, 0, 1, 1)
22590	162.457175	-2.444658	-2.047641	-2.283442	0.705775	ARDL(5, 5, 0, 1, 0)
23237	163.454078	-2.444606	-2.024235	-2.273907	0.707799	ARDL(5, 4, 1, 1, 1)
20322	166.372081	-2.443228	-1.952795	-2.244079	0.713267	ARDL(5, 8, 1, 1, 0)
23310	162.364506	-2.443101	-2.046083	-2.281885	0.705317	ARDL(5, 4, 0, 2, 0)
22589	163.359158	-2.443011	-2.022639	-2.272311	0.707333	ARDL(5, 5, 0, 1, 1)
21859	165.330864	-2.442536	-1.975456	-2.252869	0.711152	ARDL(5, 6, 0, 1, 2)
16757	163.330707	-2.442533	-2.022161	-2.271833	0.707193	ARDL(6, 4, 0, 1, 1)
23317	163.324026	-2.442421	-2.022049	-2.271721	0.707160	ARDL(5, 4, 0, 1, 2)
21851	165.264300	-2.441417	-1.974337	-2.251751	0.710829	ARDL(5, 6, 0, 2, 1)
15218	166.241922	-2.441041	-1.950607	-2.241891	0.712639	ARDL(6, 6, 1, 1, 1)
13841	167.233977	-2.440907	-1.927120	-2.232274	0.714477	ARDL(6, 8, 0, 1, 1)
21050	166.229864	-2.440838	-1.950405	-2.241688	0.712581	ARDL(5, 7, 1, 1, 1)
13760	168.171363	-2.439855	-1.902713	-2.221739	0.716012	ARDL(6, 8, 1, 1, 1)
23309	163.121379	-2.439015	-2.018643	-2.268315	0.706161	ARDL(5, 4, 0, 2, 1)
21051	165.116993	-2.438941	-1.971861	-2.249275	0.710112	ARDL(5, 7, 1, 1, 0)
20403	165.109459	-2.438814	-1.971735	-2.249148	0.710076	ARDL(5, 8, 0, 1, 0)
21132	164.099734	-2.438651	-1.994925	-2.258468	0.708062	ARDL(5, 7, 0, 1, 0)
26235	157.079603	-2.438313	-2.158065	-2.324513	0.692994	ARDL(5, 0, 0, 1, 0)
16677	163.054906	-2.437898	-2.017526	-2.267198	0.705832	ARDL(6, 4, 1, 1, 0)
21778	166.014047	-2.437211	-1.946777	-2.238061	0.711536	ARDL(5, 6, 1, 1, 2)
15300	163.983929	-2.436705	-1.992979	-2.256522	0.707494	ARDL(6, 6, 0, 1, 0)
21698	165.983775	-2.436702	-1.946269	-2.237553	0.711389	ARDL(5, 6, 2, 1, 1)
21770	165.974644	-2.436549	-1.946115	-2.237399	0.711345	ARDL(5, 6, 1, 2, 1)
15219	164.957246	-2.436256	-1.969177	-2.246590	0.709333	ARDL(6, 6, 1, 1, 0)
22509	162.907071	-2.435413	-2.015041	-2.264713	0.705100	ARDL(5, 5, 1, 1, 0)
20401	166.887205	-2.435079	-1.921292	-2.226446	0.712808	ARDL(5, 8, 0, 1, 2)
20393	166.885998	-2.435059	-1.921271	-2.226426	0.712802	ARDL(5, 8, 0, 2, 1)
23229	162.877904	-2.434923	-2.014551	-2.264223	0.704956	ARDL(5, 4, 1, 2, 0)
23157	162.861874	-2.434653	-2.014282	-2.263954	0.704876	ARDL(5, 4, 2, 1, 0)
20312	167.836336	-2.434224	-1.897083	-2.216108	0.714409	ARDL(5, 8, 1, 2, 1)
14570	165.833749	-2.434181	-1.943747	-2.235031	0.710661	ARDL(6, 7, 0, 1, 1)
20320	167.825248	-2.434038	-1.896896	-2.215922	0.714355	ARDL(5, 8, 1, 1, 2)
20240	167.824541	-2.434026	-1.896884	-2.215910	0.714352	ARDL(5, 8, 2, 1, 1)
21771	164.770929	-2.433125	-1.966045	-2.243459	0.708421	ARDL(5, 6, 1, 2, 0)
13761	166.770203	-2.433113	-1.919325	-2.224480	0.712243	ARDL(6, 8, 1, 1, 0)
26234	157.726818	-2.432383	-2.128782	-2.309100	0.693451	ARDL(5, 0, 0, 1, 1)

25506	157.722815	-2.432316	-2.128714	-2.309033	0.693430	ARDL(5, 1, 0, 1, 0)
21852	163.719331	-2.432258	-1.988532	-2.252075	0.706190	ARDL(5, 6, 0, 2, 0)
23236	163.690881	-2.431780	-1.988054	-2.251597	0.706049	ARDL(5, 4, 1, 1, 2)
21699	164.653529	-2.431152	-1.964072	-2.241485	0.707845	ARDL(5, 6, 2, 1, 0)
16029	162.645576	-2.431018	-2.010646	-2.260318	0.703802	ARDL(6, 5, 0, 1, 0)
16676	163.642053	-2.430959	-1.987233	-2.250776	0.705808	ARDL(6, 4, 1, 1, 1)
16749	162.636482	-2.430865	-2.010494	-2.260166	0.703756	ARDL(6, 4, 0, 2, 0)
19674	157.629188	-2.430743	-2.127141	-2.307460	0.692947	ARDL(6, 0, 0, 1, 0)
15298	165.628406	-2.430730	-1.940296	-2.231580	0.709660	ARDL(6, 6, 0, 1, 2)
22588	163.625107	-2.430674	-1.986948	-2.250491	0.705724	ARDL(5, 5, 0, 1, 2)
10197	162.614762	-2.430500	-2.010129	-2.259801	0.703648	ARDL(7, 4, 0, 1, 0)
22508	163.610566	-2.430430	-1.986704	-2.250247	0.705652	ARDL(5, 5, 1, 1, 1)
26154	157.602185	-2.430289	-2.126687	-2.307006	0.692808	ARDL(5, 0, 1, 1, 0)
15290	165.596495	-2.430193	-1.939760	-2.231044	0.709505	ARDL(6, 6, 0, 2, 1)
16756	163.569244	-2.429735	-1.986010	-2.249552	0.705448	ARDL(6, 4, 0, 1, 2)
14489	166.566982	-2.429697	-1.915910	-2.221064	0.711258	ARDL(6, 7, 1, 1, 1)
8738	165.554189	-2.429482	-1.939049	-2.230333	0.709298	ARDL(7, 6, 0, 1, 1)
21130	165.515544	-2.428833	-1.938399	-2.229683	0.709109	ARDL(5, 7, 0, 1, 2)
16028	163.508555	-2.428715	-1.984990	-2.248532	0.705147	ARDL(6, 5, 0, 1, 1)
13842	165.508234	-2.428710	-1.938276	-2.229560	0.709073	ARDL(6, 8, 0, 1, 0)
20313	166.502615	-2.428615	-1.914828	-2.219982	0.710946	ARDL(5, 8, 1, 2, 0)
21122	165.500646	-2.428582	-1.938149	-2.229433	0.709036	ARDL(5, 7, 0, 2, 1)
14490	165.495403	-2.428494	-1.938061	-2.229345	0.709011	ARDL(6, 7, 1, 1, 0)
14571	164.480681	-2.428247	-1.961167	-2.238580	0.706995	ARDL(6, 7, 0, 1, 0)
22581	162.461271	-2.427921	-2.007549	-2.257221	0.702883	ARDL(5, 5, 0, 2, 0)
23156	163.455922	-2.427831	-1.984105	-2.247648	0.704886	ARDL(5, 4, 2, 1, 1)
23228	163.454799	-2.427812	-1.984086	-2.247629	0.704881	ARDL(5, 4, 1, 2, 1)
23301	162.379399	-2.426545	-2.006173	-2.255845	0.702474	ARDL(5, 4, 0, 3, 0)
22580	163.375830	-2.426485	-1.982759	-2.246302	0.704489	ARDL(5, 5, 0, 2, 1)
20241	166.375507	-2.426479	-1.912692	-2.217846	0.710327	ARDL(5, 8, 2, 1, 0)
23316	163.365038	-2.426303	-1.982578	-2.246120	0.704435	ARDL(5, 4, 0, 1, 3)
15209	166.356823	-2.426165	-1.912378	-2.217532	0.710236	ARDL(6, 6, 1, 2, 1)
18945	158.342633	-2.425927	-2.098971	-2.293160	0.693717	ARDL(6, 1, 0, 1, 0)
10196	163.341728	-2.425911	-1.982186	-2.245728	0.704319	ARDL(7, 4, 0, 1, 1)
21842	165.339925	-2.425881	-1.935448	-2.226732	0.708249	ARDL(5, 6, 0, 3, 1)
21858	165.337352	-2.425838	-1.935404	-2.226688	0.708237	ARDL(5, 6, 0, 1, 3)
16748	163.333074	-2.425766	-1.982040	-2.245583	0.704276	ARDL(6, 4, 0, 2, 1)
21850	165.332203	-2.425751	-1.935318	-2.226602	0.708211	ARDL(5, 6, 0, 2, 2)
23308	163.326418	-2.425654	-1.981928	-2.245471	0.704243	ARDL(5, 4, 0, 2, 2)
15217	166.310108	-2.425380	-1.911592	-2.216747	0.710009	ARDL(6, 6, 1, 1, 2)
15137	166.293680	-2.425104	-1.911316	-2.216471	0.709929	ARDL(6, 6, 2, 1, 1)
13751	168.289232	-2.425029	-1.864534	-2.197430	0.713591	ARDL(6, 8, 1, 2, 1)
19673	158.281140	-2.424893	-2.097937	-2.292127	0.693401	ARDL(6, 0, 0, 1, 1)
15210	165.275634	-2.424801	-1.934367	-2.225651	0.707934	ARDL(6, 6, 1, 2, 0)
13832	167.269575	-2.424699	-1.887557	-2.206583	0.711675	ARDL(6, 8, 0, 2, 1)
21041	166.258062	-2.424505	-1.910718	-2.215872	0.709755	ARDL(5, 7, 1, 2, 1)
21042	165.251614	-2.424397	-1.933963	-2.225247	0.707816	ARDL(5, 7, 1, 2, 0)
25505	158.244958	-2.424285	-2.097329	-2.291519	0.693214	ARDL(5, 1, 0, 1, 1)
8657	166.241942	-2.424234	-1.910447	-2.215601	0.709676	ARDL(7, 6, 1, 1, 1)
21049	166.240521	-2.424210	-1.910423	-2.215578	0.709670	ARDL(5, 7, 1, 1, 2)
24048	159.240363	-2.424208	-2.073898	-2.281958	0.695403	ARDL(5, 3, 0, 1, 0)
7280	167.235862	-2.424132	-1.886991	-2.206016	0.711512	ARDL(7, 8, 0, 1, 1)
13840	167.235222	-2.424121	-1.886980	-2.206005	0.711509	ARDL(6, 8, 0, 1, 2)
20969	166.230178	-2.424037	-1.910249	-2.215404	0.709619	ARDL(5, 7, 2, 1, 1)
13679	168.185197	-2.423281	-1.862785	-2.195681	0.713089	ARDL(6, 8, 2, 1, 1)
13759	168.177190	-2.423146	-1.862651	-2.195547	0.713051	ARDL(6, 8, 1, 1, 2)
15291	164.172845	-2.423073	-1.955993	-2.233407	0.705476	ARDL(6, 6, 0, 2, 0)

7199	168.171806	-2.423056	-1.862560	-2.195456	0.713025	ARDL(7, 8, 1, 1, 1)
25425	158.161338	-2.422880	-2.095924	-2.290113	0.692783	ARDL(5, 1, 1, 1, 0)
20394	165.159138	-2.422843	-1.932409	-2.223693	0.707362	ARDL(5, 8, 0, 2, 0)
21123	164.157859	-2.422821	-1.955742	-2.233155	0.705401	ARDL(5, 7, 0, 2, 0)
23300	163.152501	-2.422731	-1.979006	-2.242548	0.703378	ARDL(5, 4, 0, 3, 1)
21761	166.143608	-2.422582	-1.908794	-2.213949	0.709196	ARDL(5, 6, 1, 3, 1)
20970	165.125526	-2.422278	-1.931844	-2.223128	0.707196	ARDL(5, 7, 2, 1, 0)
16668	163.120849	-2.422199	-1.978474	-2.242016	0.703220	ARDL(6, 4, 1, 2, 0)
13752	167.117367	-2.422141	-1.884999	-2.204024	0.710937	ARDL(6, 8, 1, 2, 0)
10116	163.102271	-2.421887	-1.978161	-2.241704	0.703127	ARDL(7, 4, 1, 1, 0)
26226	157.097716	-2.421810	-2.118209	-2.298527	0.690192	ARDL(5, 0, 0, 2, 0)
19593	158.097591	-2.421808	-2.094853	-2.289042	0.692453	ARDL(6, 0, 1, 1, 0)
26153	158.096439	-2.421789	-2.094833	-2.289022	0.692447	ARDL(5, 0, 1, 1, 1)
15948	163.076171	-2.421448	-1.977723	-2.241265	0.702997	ARDL(6, 5, 1, 1, 0)
16596	163.058139	-2.421145	-1.977420	-2.240962	0.702907	ARDL(6, 4, 2, 1, 0)
21769	166.039556	-2.420833	-1.907045	-2.212200	0.708687	ARDL(5, 6, 1, 2, 2)
21777	166.039476	-2.420832	-1.907044	-2.212199	0.708687	ARDL(5, 6, 1, 1, 3)
21697	166.030035	-2.420673	-1.906885	-2.212040	0.708641	ARDL(5, 6, 2, 1, 2)
21689	166.018222	-2.420474	-1.906687	-2.211841	0.708583	ARDL(5, 6, 2, 2, 1)
20159	168.001963	-2.420201	-1.859706	-2.192602	0.712205	ARDL(5, 8, 3, 1, 1)
8739	163.987511	-2.419958	-1.952879	-2.230292	0.704557	ARDL(7, 6, 0, 1, 0)
15138	164.984781	-2.419912	-1.929479	-2.220763	0.706503	ARDL(6, 6, 2, 1, 0)
21617	165.983776	-2.419895	-1.906108	-2.211262	0.708414	ARDL(5, 6, 3, 1, 1)
20303	167.968833	-2.419644	-1.859149	-2.192045	0.712044	ARDL(5, 8, 1, 3, 1)
8658	164.962939	-2.419545	-1.929112	-2.220396	0.706395	ARDL(7, 6, 1, 1, 0)
23220	162.940322	-2.419165	-1.975439	-2.238982	0.702318	ARDL(5, 4, 1, 3, 0)
20384	166.931407	-2.419015	-1.881874	-2.200899	0.710032	ARDL(5, 8, 0, 3, 1)
22500	162.920369	-2.418830	-1.975104	-2.238647	0.702218	ARDL(5, 5, 1, 2, 0)
22428	162.907578	-2.418615	-1.974889	-2.238432	0.702154	ARDL(5, 5, 2, 1, 0)
20400	166.906734	-2.418601	-1.881459	-2.200484	0.709912	ARDL(5, 8, 0, 1, 3)
16675	163.906081	-2.418590	-1.951510	-2.228923	0.704152	ARDL(6, 4, 1, 1, 2)
17487	159.896271	-2.418425	-2.044761	-2.266692	0.695817	ARDL(6, 3, 0, 1, 0)
22507	163.891770	-2.418349	-1.951269	-2.228683	0.704081	ARDL(5, 5, 1, 1, 2)
14561	165.890318	-2.418325	-1.904537	-2.209692	0.707956	ARDL(6, 7, 0, 2, 1)
20392	166.887386	-2.418275	-1.881134	-2.200159	0.709817	ARDL(5, 8, 0, 2, 2)
21762	164.884631	-2.418229	-1.927796	-2.219079	0.706008	ARDL(5, 6, 1, 3, 0)
23148	162.879658	-2.418146	-1.974420	-2.237963	0.702014	ARDL(5, 4, 2, 2, 0)
23076	162.863619	-2.417876	-1.974150	-2.237693	0.701934	ARDL(5, 4, 3, 1, 0)
18944	158.862483	-2.417857	-2.067547	-2.275607	0.693462	ARDL(6, 1, 0, 1, 1)
14569	165.850675	-2.417658	-1.903871	-2.209026	0.707761	ARDL(6, 7, 0, 1, 2)
20231	167.846319	-2.417585	-1.857090	-2.189986	0.711451	ARDL(5, 8, 2, 2, 1)
14481	165.843376	-2.417536	-1.903748	-2.208903	0.707725	ARDL(6, 7, 1, 2, 0)
20311	167.841513	-2.417504	-1.857009	-2.189905	0.711427	ARDL(5, 8, 1, 2, 2)
8009	165.835949	-2.417411	-1.903623	-2.208778	0.707689	ARDL(7, 7, 0, 1, 1)
20239	167.832492	-2.417353	-1.856857	-2.189753	0.711384	ARDL(5, 8, 2, 1, 2)
20319	167.828426	-2.417284	-1.856789	-2.189685	0.711364	ARDL(5, 8, 1, 1, 3)
21690	164.806448	-2.416915	-1.926482	-2.217766	0.705622	ARDL(5, 6, 2, 2, 0)
26233	157.804681	-2.416885	-2.089930	-2.284119	0.690936	ARDL(5, 0, 0, 1, 2)
16027	163.793427	-2.416696	-1.949617	-2.227030	0.703591	ARDL(6, 5, 0, 1, 2)
3636	162.782909	-2.416519	-1.972794	-2.236337	0.701529	ARDL(8, 4, 0, 1, 0)
7200	166.777270	-2.416425	-1.879283	-2.198308	0.709280	ARDL(7, 8, 1, 1, 0)
24047	159.774546	-2.416379	-2.042715	-2.264646	0.695195	ARDL(5, 3, 0, 1, 1)
24777	157.773708	-2.416365	-2.089409	-2.283598	0.690775	ARDL(5, 2, 0, 1, 0)
13680	166.770293	-2.416307	-1.879166	-2.198191	0.709246	ARDL(6, 8, 2, 1, 0)
23235	163.759776	-2.416131	-1.949051	-2.226464	0.703424	ARDL(5, 4, 1, 1, 3)
23967	159.753991	-2.416033	-2.042370	-2.264300	0.695089	ARDL(5, 3, 1, 1, 0)
19665	157.751211	-2.415987	-2.089031	-2.283220	0.690658	ARDL(6, 0, 0, 2, 0)

15947	163.750375	-2.415973	-1.948893	-2.226306	0.703377	ARDL(6, 5, 1, 1, 1)
25497	157.747880	-2.415931	-2.088975	-2.283164	0.690641	ARDL(5, 1, 0, 2, 0)
21843	163.745313	-2.415888	-1.948808	-2.226221	0.703352	ARDL(5, 6, 0, 3, 0)
26225	157.726840	-2.415577	-2.088621	-2.282811	0.690531	ARDL(5, 0, 0, 2, 1)
18864	158.724192	-2.415533	-2.065223	-2.273283	0.692749	ARDL(6, 1, 1, 1, 0)
14480	166.710066	-2.415295	-1.878154	-2.197179	0.708951	ARDL(6, 7, 1, 2, 1)
13833	165.703370	-2.415183	-1.901395	-2.206550	0.707037	ARDL(6, 8, 0, 2, 0)
9468	162.694324	-2.415031	-1.971305	-2.234848	0.701085	ARDL(7, 5, 0, 1, 0)
23155	163.693660	-2.415019	-1.947940	-2.225353	0.703094	ARDL(5, 4, 2, 1, 2)
23227	163.691078	-2.414976	-1.947897	-2.225310	0.703081	ARDL(5, 4, 1, 2, 2)
14562	164.688929	-2.414940	-1.924506	-2.215790	0.705040	ARDL(6, 7, 0, 2, 0)
16020	162.684235	-2.414861	-1.971135	-2.234678	0.701034	ARDL(6, 5, 0, 2, 0)
15289	165.678292	-2.414761	-1.900974	-2.206128	0.706913	ARDL(6, 6, 0, 2, 2)
15281	165.671069	-2.414640	-1.900852	-2.206007	0.706878	ARDL(6, 6, 0, 3, 1)
10115	163.666594	-2.414565	-1.947485	-2.224898	0.702959	ARDL(7, 4, 1, 1, 1)
10188	162.664721	-2.414533	-1.970808	-2.234350	0.700936	ARDL(7, 4, 0, 2, 0)
22587	163.655544	-2.414379	-1.947299	-2.224713	0.702904	ARDL(5, 5, 0, 1, 3)
16740	162.654490	-2.414361	-1.970636	-2.234178	0.700884	ARDL(6, 4, 0, 3, 0)
13113	157.654212	-2.414357	-2.087401	-2.281590	0.690153	ARDL(7, 0, 0, 1, 0)
21618	164.653547	-2.414345	-1.923912	-2.215196	0.704864	ARDL(5, 6, 3, 1, 0)
16667	163.651638	-2.414313	-1.947234	-2.224647	0.702884	ARDL(6, 4, 1, 2, 1)
16595	163.648788	-2.414265	-1.947186	-2.224599	0.702870	ARDL(6, 4, 2, 1, 1)
26145	157.635073	-2.414035	-2.087079	-2.281268	0.690053	ARDL(5, 0, 1, 2, 0)
22579	163.633846	-2.414014	-1.946935	-2.224348	0.702795	ARDL(5, 5, 0, 2, 2)
15297	165.630160	-2.413952	-1.900165	-2.205319	0.706676	ARDL(6, 6, 0, 1, 3)
8737	165.628414	-2.413923	-1.900135	-2.205290	0.706667	ARDL(7, 6, 0, 1, 2)
20318	168.617119	-2.413733	-1.829884	-2.176650	0.712135	ARDL(5, 8, 1, 1, 4)
22499	163.615521	-2.413706	-1.946627	-2.224040	0.702704	ARDL(5, 5, 1, 2, 1)
22427	163.613719	-2.413676	-1.946596	-2.224010	0.702695	ARDL(5, 5, 2, 1, 1)
19592	158.604066	-2.413514	-2.063204	-2.271264	0.692128	ARDL(6, 0, 1, 1, 1)
26073	157.603017	-2.413496	-2.086540	-2.280730	0.689886	ARDL(5, 0, 2, 1, 0)
8729	165.596824	-2.413392	-1.899604	-2.204759	0.706512	ARDL(7, 6, 0, 2, 1)
10195	163.579795	-2.413106	-1.946026	-2.223440	0.702525	ARDL(7, 4, 0, 1, 2)
16747	163.578916	-2.413091	-1.946011	-2.223425	0.702521	ARDL(6, 4, 0, 2, 2)
16755	163.578559	-2.413085	-1.946005	-2.223419	0.702519	ARDL(6, 4, 0, 1, 3)
14488	166.578068	-2.413077	-1.875935	-2.194961	0.708305	ARDL(6, 7, 1, 1, 2)
7928	166.572241	-2.412979	-1.875837	-2.194863	0.708276	ARDL(7, 7, 1, 1, 1)
14408	166.570705	-2.412953	-1.875812	-2.194837	0.708269	ARDL(6, 7, 2, 1, 1)

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