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Exchange Rates Volatility Modelling

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Master in Economics

Supervisor:

Professor Doutor José Joaquim Dias Curto, Associate Professor with Habilitation,

Department of Quantitative Methods for Management and Economics

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"Winners never quit, and quitters never win"

– Vince T. Lombardi

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Resumo

Neste estudo investigamos a relevância empírica de quebras estruturais na variância dos retornos de sete taxas de câmbio *vis-à-vis* o US Dólar no período compreendido entre 2012 e 2018. Encontramos evidência empírica da existência de quebras estruturais na variância de cinco dos sete pares em estudo, com um elevado grau de persistência e variabilidade nos parâmetros do modelo GARCH (1,1) ao longo das diferentes subamostras definidas pelas quebras estruturais. Ao analisar o momento do tempo em que estas quebras ocorrem, somos capazes de associar a maioria delas a ocorrências significativas do ponto de vista social, político e económico, quer numa escala regional quer nacional. Os nossos resultados indicam que as quebras estruturais são relevantes do ponto de visa empírico no que à modelização de retornos de taxas de câmbio diz respeito e devem ser tidos em conta aquando da realização de exercícios de previsão de volatilidade.

Palavras Chave: *Volatilidade; Taxas de Câmbio; Previsão; Retornos; GARCH*

JEL Codes**:** *C55; G11; G17*

Abstract

We investigate the empirical relevance of structural breaks in the unconditional variance of exchange rate returns for seven currency pairs *vis-à-vis* the US Dollar over the 2002 – 2018 period. We find evidence of structural breaks in the unconditional variance for five of the seven currencies under our scope with a high degree of persistence and variability in the parameter estimates of the GARCH (1,1) model across the various subsamples defined by the structural breaks. When analysing the time of occurrence of these breaks, we are able to associate a vast majority of them to relevant social, political and economic events occurring on both a regional and a global scale. Our research indicates that structural breaks are an empirically relevant feature of exchange rate volatility modelling and should be accounted for when performing volatility forecasts.

Keywords**:** *Volatility; Exchange Rates; Forecasting; Returns; GARCH*

JEL Codes**:** *C55; G11; G17*

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Introduction

Uncertainty has always played an important role in everyday decisions on a social, political and economic level. Since the subprime crisis triggered in the USA in the mid-2000's and the sovereign debt crisis that followed, a great number of efforts were made in order to incentive and establish more effective and robust risk policies, which complemented with a vast set of new financial regulatory framework, and a greater emphasis on compliance function's, aim to mitigate the probability of recurrence of an event of such magnitude in the financial sector. From a financial market standpoint, it is common to associate the term "uncertainty" to "volatility" which in turn is perceived as a measure of risk and refers to the amount of uncertainty related to the size of changes in an underlying security's or index value (Goltz et al, 2011). Volatility in the stock, bond and foreign exchange markets can be utilized as a measure of risk and its non-neglectable impact on the financial markets and their stability have an important consequence on the development of economic policy.

In an increasingly interconnected and globalized economy, exchange rates between the different currencies assume a relevant role both in a practical manner - in a vast array of fields ranging from international trade to investor's portfolio returns - and from a more theoretical standpoint as a relative indicator of a country's economic health. The ability to properly forecast future exchange rate volatility is of great importance and might provide important insight in terms of an effective asset allocation, derivative securities pricing, and dynamic hedging (Reider, 2009). Despite the increased academic interest that has arisen in the last decades towards the volatility of financial assets the impact of structural breaks on the accuracy of volatility forecasts has consistently been ignored. This is a consequence of the fact that researchers regularly assume the existence of a stable GARCH process in volatility forecasting. Nonetheless, financial markets are regularly subject to the impact of significant events that can result in breaks in the unconditional variance of exchange rate returns and are equivalent to structural breaks in the parameters governing the models of conditional volatility of exchange rate returns (Rapach and Strauss, 2008). Correspondingly, unaccounted structural breaks may result in misleading inference on the parameters of the model and can lead to a biased degree of persistence estimations in GARCH models resulting in an inaccurate track of the changes in the unconditional variance with adverse effects on volatility forecasts (Mikosh and Starica, 2004; Hillebrand, 2005; Rapach and Strauss, 2008). Researchers often favour the adoption of a fixed or expanding window when estimating GARCH models (Bollerslev, 1986) in order to generate out-of-sample volatility forecasts which have a non-neglectable impact on the accuracy of these forecasts since fixed or expanding window mechanisms do not perform well in the presence of a structural break (West and Cho, 1995). In order to mitigate this shortcoming, Starica and Granger (2005) suggest that volatility forecasts generated by a GARCH (1,1) model that allows for changes in the unconditional variance yield better results than forecasts that assume parameter stability.

The aim of this study is to (i) investigate the presence of structural breaks in the variance of exchange rate returns of the Euro, Pound Sterling, Japanese Yen, Brazilian Real, Russian Ruble, Indian Rupee and Chinese Renminbi *vis-à-vis* the US Dollar for the period between January 1st, 2002 and December 31st, 2018 (ii) identify relevant events from a social, political and economic standpoint that might have contributed for the occurrence of structural breaks in volatility of the series.

This dissertation is divided in four parts and it is structured in the following manner: in Chapter 2 a literature review is made which intends to (i) give a broad perspective of the study and ever-growing research interest towards volatility modelling and forecasting in time series analysis (ii) introduce the most relevant research with respect to structural breaks identification and analysis, and present its results

In Chapter 3 we present the data and methodology utilized in this study. First, the data is presented, described and grouped accordingly between hard and soft currencies, followed by a brief descriptive statistics presentation and analysis. Next, we shed light on the methodological framework utilized in this study, by first presenting the necessary data transformation and manipulation techniques, followed by a characterization of the steps taken in the tests performed. In our in-sample tests approach we utilize a modified version of the iterated cumulative sum of squares (ICSS) algorithm originally proposed by Inclán and Tiao (1994) in order to test for the existence of (potentially multiple) structural breaks in the variance of seven exchange rates *vis-à-vis* the US Dollar. If a break is identified, a further analysis is performed in order to determine the existence of additional significant variance changes in the series, followed by a suggestive discussion regarding the economic events that might have triggered the occurrence of the break.

In Chapter 4 we present and discuss the results, which showed that in the 2002-2018 timeframe the modified ICSS algorithm identified a grand total of twenty-seven structural breaks in the unconditional variance of the seven exchange rate return series vis-à-vis the US Dollar.

In Chapter 5 we present our conclusion, followed by difficulties and limitations encountered during the course of this study and suggestions for future research.

Literature review

In this section, we are going to review the main literature on financial volatility, with a great focus on exchange rates volatility in particular. First, we will present the emergence and importance of the concept of volatility when applied to financial time series modelling. Next, we will be presenting a brief introduction of the post Bretton Woods system and predominant adoption of floating exchange rates by the most industrialized countries and an insight on some of the most relevant models of volatility modelling and their extensions. To conclude this section, we will be reviewing some of the most relevant literature regarding exchange rate volatility modelling and structural breaks identification covering a broad range of geographies and diverse methodologies.

The study of volatility has assumed a great importance over the last decades, and currently there is an ever-growing interest by individuals, governments and private companies in the ability to try to anticipate future upward or downward fluctuations of prices and rates of return of a vast array of assets such as exchange rates, interest rates, stock prices and financial derivatives, in order to effectively mitigate their exposure to adverse situations and entitle themselves with the ability to better understand and exploit possible favourable scenarios.

The first attempt to define the term volatility belongs to Louis Bachelier who characterized it as the "coefficient of nervousness" or "of instability" of the price (Bachelier, 1900). The concept of financial time series volatility that is time varying was first introduced by Mandelbrot (1963) and was the root for further studies on this topic such as the key seminal contribution that was later presented by Engle (1982) and that would shape the way that we analyse volatility until the present day.

Not long ago, the focus of most macro econometric and financial time series modelling was centered mainly on the conditional first moments, with any temporal dependencies in the higher order moments treated as a nuisance. The increased importance played by risk and uncertainty considerations in modern economic theory, urged for the development of new econometric time series techniques that would allow to model the time varying variances and covariances (Bollerslev et al. 1992). The Autoregressive Conditional Heteroskedasticy (ARCH) model proposed by Engle (1982) emerges due to the necessity to develop a model that allowed to validate Friedman’s (1977) statement that the unpredictability of inflation was the source of the economic cycles and that this uncertainty would have a severe effect on the investor’s behaviour (Furriel, 2011). It is an autoregressive model in squared returns which was pioneer by allowing for a time-dependent heteroskedasticity distribution for the asset returns (returns with non-constant volatility). This model introduced a stationary parametric and conditional approach - constant unconditional volatility - to forecast the second moment of the financial asset returns distribution based on the size of previous error terms. Under an ARCH model, if the residual return of a given asset is large in magnitude, the next period’s conditional volatility will also be large. An alternative to this model was proposed by Bollerslev – the Generalized Autoregressive Conditional Heteroskedasticy (GARCH) model - which represented a more parsimonious model that required a substantially lower number of parameters in order to adequately study the variation of volatility over time. This model acts as an extension of the ARCH and considers that the conditional variance of the error term is not only related with the previous various of the series but also with previous conditional variances (Bollerslev, 1986) and (Andersen and Bollerslev, 1998).

An exchange rate is the rate at which one currency will be exchanged for another and thus allows to determine how much of one currency can be exchange for another. As so, it refers to the tendency of the exchange rates do appreciate or depreciate over time, which in turn has direct impact on the probability of a given currency. Exchange rate volatility is measured using the standard deviation and is usually assumed to follow a normal distribution. Exchange rate regimes can be classified in two groups: fluctuating or floating and fixed or pegged. In the former, the exchange rates are determined by market forces and mechanisms of demand and supply, while in the latter the exchange rates are directly determined by the governmental bodies. After the collapse of the Bretton Woods system of fixed exchange rate in 1973, the fluctuation of exchange rates received a great deal of attention from academics, economists and policy makers since the volatility in this field had a great impact on countries’ inflation, risk management and trade and capital flow (De Grauwe, 1984) and in the design thinking process of monetary policy (Longmore and Robinson, 2004).

It is often assumed that the unconditional variance of exchange rate returns is constant, thus consisting in a stable GARCH process. Nevertheless, occasionally the financial markets are subject to unforeseen and impactful shocks, which can result in breaks in the unconditional variance of exchange rate returns and are equivalent to structural breaks in the parameters of the GARCH process governing the conditional volatility of exchange rate returns. “Theoretical studies show that structural breaks have potentially important implications for estimated GARCH models of exchange rate volatility, which are typically highly persistent. By failing to account for structural breaks, estimated GARCH models of exchange rate volatility in the extant literature can overstate the degree of persistence in exchange rate volatility.” (Rapach and Strauss, 2008). Given the increased attention and interest that predictive models have received lately – and considering the fact that predictive models are estimated using long data intervals – the study of the structural stability of its parameters represents an important research topic. Pesaran and Timmerman (2002) identified a number of reasons that could lead up to the occurrence of structural break and present a source of instability in predictive regression models, such as: major changes in market sentiment, regime changes in monetary policy, changes in debt management policies and speculative bubbles.

The investigation of structural breaks in financial time series has resulted in the emergence of significant literature covering commodities, equity and exchange rates.

When modelling oil price volatility for both West Texas Intermediate and Brent, Salisu and Fasanya (2013) found two structural breaks which coincide with the Iraqui-Kuwait conflict in 1990 and the financial crisis in 2008 – events that impacted supply and demand and subsequently spot and futures contracts. When analysing volatility spill-over effects between oil and gold returns between July 1st 1993 and June 30th 2010, Ewing and Malik (2003) employed a modified version of the ICSS algorithm and identified seven and nine break points in oil and gold returns, respectively – with the majority of them occurring in the 2007-2010 period.

Lamoureux and Lastrapes (1990) demonstrated that breaks in the unconditional level of volatility drove the estimated persistence of volatility towards integrated GARCH model of Engle and Bollerslev (1986). They partitioned the sample into a fixed number of equally spaced volatility episodes in which unconditional volatility is fixed for a sample of 30 individual stocks. The point estimates of volatility persistence were greatly reduced after allowing for these ‘breaks’ in volatility to occur. Babikir et al (2012) investigated the empirical relevance of structural breaks in forecasting stock return volatility using both in-sample and out-of-sample test on daily returns of the Johannesburg Stock Exchange – South Africa – in the period comprised between February 7th 1995 and August 25th 2010 and found evidence of structural breaks in the unconditional variance of the stock returns series with high levels of persistence and variability in the parameter estimates of the GARCH (1,1) across the sub-samples defined by the structural breaks. When investigating the existence of structural breaks in the unconditional variance of stock returns using weekly data from the Shanghai Stock Exchange and Shenzhen Stock Exchange over the 1990-2011 horizon, Ni et al. (2016) identify three structural breaks in each of the index series and associated their occurrence to proactive government policy. Yıldırım and Çelik (2020) utilized stock market data from indexes representative of twelve countries, over the 2013-2019 period, in order to test for the existence of structural breaks and found no evidence of breaks in the South African, Mexican, Argentinian and Qatari series – having also concluded that the level of persistence in volatility is greater in the Indonesian, Indian, Brazilian, Russian and Turkish indexes.

Andreu and Ghysels (2002) were able to identify a strong evidence of structural breaks in volatility in 1997 – which corresponded to the Asian currency crisis - while applying GARCH models to daily data on four international stock indices and five-minute returns on the Yen/Dollar exchange rate. Malik (2003) develops a structural break test based on the ICSS and analysed five exchange rates from January 1990 to September 2000 using this test. He identified a number of structural breaks in the data, which, after being accounted for, helped reduce the persistence of the volatility shocks. Rapach and Strauss (2008) tested the empirical relevance of structural breaks for GARCH models of exchange rate volatility using both in-sample and out-of-sample tests. Their research suggests that structural breaks are an empirically relevant phenom of US Dollar exchange rate volatility and that accounting for structural breaks in the unconditional variance of the exchange rate returns helps to improve the out-of-sample forecasts of exchange rate volatility.

A vast array of previous research substantiates the adequacy of the GARCH family of models in effectively modelling and forecasting time varying volatility in financial time series. When analysing daily data of five currencies *vis-à-vis* the US Dollar for the period between 1974 and 1983 Hsieh (1989) concluded that GARCH (1,1) and EGARCH (1,1) were the most efficient options to remove conditional heteroskedasticity from daily exchange rate movements. Also, Andreea C (2016) modelled exchange rate volatility of daily returns for EUR/RON, from 1999 to 2016 using both symmetric and asymmetric GARCH models and concluded that, the best fitted model for estimating daily returns of EUR/RON exchange rate is EGARCH (2,1). Ramzan et al. (2012) concluded that GARCH family of models capture the volatility and leverage effect in the exchange rate returns and provides a model with a good forecasting performance when analysing Pakistani monthly exchange rates from July 1981 up to May 2010 – with GARCH (1,2) providing the best fit to remove the persistence in volatility while EGARCH (1,2) successfully overcome the leverage effect in the exchange rate returns.

In the research performed by Babikir et al (2012) on daily returns of the Johannesburg Stock Exchange they combined both benchmark and competing models that accommodate structural breaks in volatility and concluded that in general the asymmetric models failed to outperform the GARCH (1,1) model. In the same sense - and using data from the 1997-2015 period - Bosnjak (2016) concluded that GARCH (1,1) and GARCH (2,1) are the best fitted models for the EUR/HRK and USD/HRK, respectively. Literature also suggests that models that allow for adjustments to the estimation window do better accommodate potential structural breaks in the unconditional variance of exchange rate returns in both developed and developing countries (Rapach and Strauss, 2008; De Gaetano, 2018).

Methods

In this section we will introduce the data and methodology utilized in this analysis. First, we present and describe the data, providing a general overview accompanied by a descriptive statistical analysis for each of the seven exchange rates utilized in this study. Next, we will present the methodological framework that we will be using in order to identify eventual structural breaks in the exchange rates variance across the period in analysis.

Data

The raw data utilized in this research consists of the closing price of the daily exchange rate of seven currencies *vis-à-vis* the U.S. Dollar in the period between January 1st, 2002 and December 31st, 2018.

The currencies under the scope of our analysis are as follows:

- Euro (€) - EUR
- Pound Sterling (£) - GBP
- Japanese Yen (¥) - JPY
- Brazilian Real (R$) - BRL
- Russian Ruble (₽) - RUB
- Indian Rupee (₹) - INR
- Chinese Renminbi (¥) – CNY

In economic terms is common to distinguish currencies between hard and soft when they exhibit a set of characteristics. The main characteristics of hard currencies are directly linked to their stability and convertibility: hard currencies denote a stable behaviour, exhibiting a generally low degree of volatility. Currencies with such characteristics generally represent robust economies and developed countries, which exhibit a low inflation level due to an adequate monetary and fiscal policies, resulting in an increased confidence and attractiveness among investors, which improves its liquidity and helps to establish hard currencies as a widely accepted form of payment and foreign-exchange reserves. On the other hand, soft currencies' value often fluctuates, exhibiting a substantial degree of volatility. These types of currencies generally represent developing economies where inflation coped with a less effective monetary and fiscal policies, and social and political unpredictability, diminishes the investors' confidence in it, resulting in a less liquid and attractive currency that is not commonly utilized as a form of payment neither as foreign-exchange reserve.

In this study we may clearly divide our data between hard and soft currencies, as shown in Table 1 below:

Hard Currencies	**Soft Currencies**
EUR	BRL
GBP	RUB
JPY	INR
	CNY

Table 1 - *Separation between Hard and Soft Currencies*

To finalise this section, we will be presenting and briefly discussing the descriptive statistics analysis performed on the seven currency pairs under the scope of this study. As one can see in Table 2, the descriptive statistics reveal the usual properties of financial return data, with a small mean dominated by a large standard deviation given that all of the mean returns are small, none of them being significantly different than zero, with the GBP, BRL, INR and RUB series exhibiting a slight decline over time. The skewness values reveal that the empirical distribution of returns is asymmetric, with the GBP, BRL, INR and RUB being negatively skewed and the GBP and RUB being the largest in magnitude. All currency pairs except EUR/USD reveal a high degree of excess kurtosis which reveals the existence of heavy tails - in line with the stylised facts regarding financial data analysis. We use the Modified Ljung-Box test statistic to test for autocorrelation in returns, by analysing the p-values, we conclude that the residuals of our time series are linearly independent for six of the seven exchange rate return series (except the CNY/USD series). In regard to the squared returns, the Ljung-box test results reveal serial correlation, and The Lagrange multiplier provides significant evidence of ARCH effects.

Exchange Rate Returns

	EUR	GBP	JPY	BRL	CNY	INR	RUB
Mean	0.006	-0.003	0.004	-0.012	0.004	-0.008	-0.019
	(0.009)	(0.009)	(0.009)	(0.016)	(0.002)	(0.007)	(0.012)
Standard Deviation	0.602	0.582	0.626	1.075	0.144	0.442	0.811
	(0.009)	(0.016)	(0.012)	(0.027)	(0.005)	(0.011)	(0.039)
Skewness	0.042	-0.891	0.051	-0.128	0.207	-0.158	-0.372
	(0.083)	(0.612)	(0.188)	(0.263)	(0.807)	(0.199)	(1.033)
Kurtosis	1.700	11.792	4.255	6.574	23.366	6.279	30.349
	(0.258)	(8.365)	(1.130)	(1.651)	(7.761)	(1.081)	(10.096)
Minimum	-2.434	-8.395	-5.474	-7.362	-1.836	-3.178	-11.720
Maximum	3.450	3.001	3.811	10.310	2.032	3.473	11.953
Modified Ljung-Box	11.796	17.688	22.066	21.889	31.706	23.487	9.446
(r=20)	[0.923]	[0.608]	[0.337]	[0.347]	[0.047]	[0.265]	[0.977]

Squared Exchange Rate Returns

	EUR	GBP	JPY	BRL	CNY	INR	RUB
Ljung-Box (r=20)	1248.424	414.157	913.258	3431.396	301.183	1785.366	3955.371
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH Lagrange	138.133	131.513	150.445	704.235	112.733	264.606	1030.016
multiplier (q=2)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH Lagrange	318.931	206.415	227.775	882.757	146.314	530.636	1574.833
multiplier (q=10)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: Returns are defined as 100 times the log-differences of the daily closing US Dollar exchange rates *vis-à-vis* seven other currencies. Heteroskedastic and autocorrelation consistent standard errors for the mean, standard deviation, skewness and kurtosis are computed as in West and Cho (2005) and presented in parentheses. *P*-values are given in brackets. ARCH Lagrange multiplier statistics correspond to a test of the null hypothesis of no ARCH effects from lag orders 1 through *q*.

Table 2 **-** *Descriptive Statistics*

Methodology

In order to investigate the presence of structural breaks in the unconditional variance of the exchange rate returns we employ a modified version of the iterated cumulative sum of squares algorithm originally proposed by Inclán and Tiao (1994). Building on insights from Bollerslev (1986), Inclán and Tiao (1994), West and Cho (1995) and Sansó et al. (2004), we follow closely the econometric methodology utilized by Rapach and Strauss (2008).

Let A_t denote the nominal exchange rate at the end of period t so that the daily percentage returns of the exchange rates from the period $t-1$ to t be denoted by:

$$a_t = 100 * \log\left[\frac{A_t}{A_{t-1}}\right] \qquad (1)$$

Where t = 0,1 … T.

In order to test for the existence of a (single) structural break in the unconditional variance of a time series - which implies that the conditional volatility process is governed by an unstable GARCH process - Inclán and Tiao (1994) developed and proposed the cumulative sum of squares statistic to test the null hypothesis of a constant unconditional variance. The Inclán and Tiao (IT) test statistic is as follows:

$$IT = max\left|\left(\frac{T}{2}\right)^{0.5} * D_k\right| \qquad (2)$$

Where $D_k = \left(\frac{C_k}{C_t}\right) - \left(\frac{k}{T}\right)$ is the centered cumulative sum of squares for $k = 1, \ldots, T$, with $C_k = \sum_{t=1}^{k} a_t^2$ being the cumulative sum of squares of the series of uncorrelated random variables with mean zero and variance $\sigma_t^2, t = 1, \ldots, T$.

In order to identify a possible variance changepoint, the absolute variance of the series is maximized, $max_k|D_k|$, so that in case the maximum absolute value exceeds a predetermined threshold at a given point of time, we take the moment of occurrence k^* as the estimate of the moment of the occurrence of the structural break.

If the aim of the research is to investigate the existence of several variance change points in a time series, Inclán and Tiao (1994) propose the application of an iterative process based on the successive application of the centred cumulative sum of squares procedure described previously to various pieces of the series as multiple changepoints are identified.

One shortcoming of the *IT* statistic is that it was designed for *i.i.d* processes. Nevertheless, return processes turn out to be characterized by temporal dependencies. In previous studies done by Andreou and Ghysels (2002), Sansó et al. (2004) and de Pooter and van Dijk (2004) has been pointed out that the *IT* statistic can be substantially oversized when applied to dependent processes – such as GARCH. As a result, and in order to allow for dependent processes under the null hypothesis, Sansó et al. (2004) proposed a non-parametric adjustment to the original *IT* statistic based on the Bartlett Kernel, the adjusted Inclán and Tiao statistic:

$$AIT = max|T^{-0.5} * G_k| \tag{3}$$

Where $G_k = \hat{\lambda}^{-0.5}[C_k - \left(\frac{k}{T}\right) * C_t$, with $\hat{\lambda} = \hat{\gamma}_0 + 2\sum_{l=1}^{m}[1 - l(m+1)^{-1}] * \hat{\gamma}_l$, where $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(e_t^2 - \hat{\sigma}^2)\,(e_{t-l}^2 - \hat{\sigma}^2)$, and $\hat{\sigma}^2 = \frac{C_t}{T}$ with m being selected following Newey and West (1994).

In the present study we employ the ICSS algorithm based upon the AIT statistic – the modified cumulative sum of squares algorithm – for the 5% significance level in order to test for multiple structural breaks in the unconditional variance of the seven exchange rate return series under the scope of our research. If the existence of a structural break is detected, we estimate GARCH (1,1) models over the various subsamples defined by the structural breaks and compare them to a GARCH (1,1) model estimated over the entire sample.

The GARCH (1,1) model specification for a_t with conditional and conditional mean zero is given by:

$$e_t = h_t^{0.5} * \varepsilon_t \tag{4}$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \tag{5}$$

Where $\varepsilon_t$is *i.i.d.* with mean zero and unit variance. In order to ensure that the conditional variance $h_t$is positive, we require that $\omega > 0$ and $\alpha, \beta \geq 0$. We will be estimating the GARCH (1,1) model using the quasi-maximum likelihood estimation (QMLE) which have shown to be consistent and asymptotically normal under certain conditions (Ling and McAleer, 2003; Straumann, 2005) where the likelihood function $\varepsilon_t \sim N(0,1)$ is used and $\omega > 0$ and $\alpha, \beta \geq 0$ are imposed as restrictions.

Results and Discussion

The modified version of the ICSS algorithm that we employed identified a grand total of twenty-seven structural breaks in the exchange rate return series of seven currencies *vis-à-vis* the US Dollar for the period between 2002 and 2018. Table 3 below shows the break distribution by currency pair and time of occurrence.

EUR	GBP	JPY	BRL	CNY	INR	RUB
March 2003		December 2007		March 2003	May 2008	September 2008
September 2004		July 2010		February 2015	August 2015	October 2009
August 2006		January 2018		April 2018	May 2018	February 2015
December 2007						May 2015
November 2008						October 2016
February 2009						
August 2009						
June 2010						
February 2012						
October 2013						
June 2014						
December 2014						
April 2016						

Table 3 - *Structural Break Distribution by Currency Pair and Time of Occurrence*

A total of thirteen structural breaks were identified for the EURUSD series; five structural breaks for the RUBUSD; three for the JPYUSD, CNYUSD and INRUSD; and no breaks were identified for the GBPUSD and BRLUSD pairs. Overall, we observe that the modified ICSS algorithm identified breaks in the variance of five of the seven currencies in analysis.

Without surprise, the breakpoints identified by the algorithm coincide with periods of considerable financial turmoil which leads us to believe that a significant amount of them may have been triggered by economic phenomena on a global scale, but also by specific economic, social and political events of a regional and/or national level. Figures 1 to 7 below display the plot of the stock returns series and three standard-deviation bands defined by the structural breaks identified by the modified ICSS algorithm.

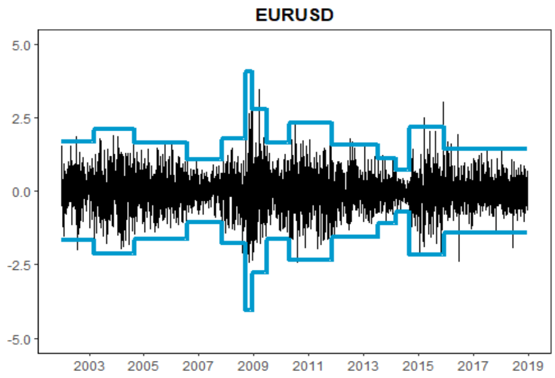

Figure 1 *- Structural Breaks Identified for EURUSD*

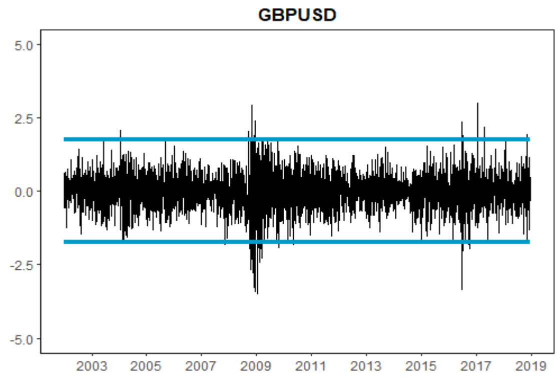

Figure 2 *- Structural Breaks Identified for GBPUSD*

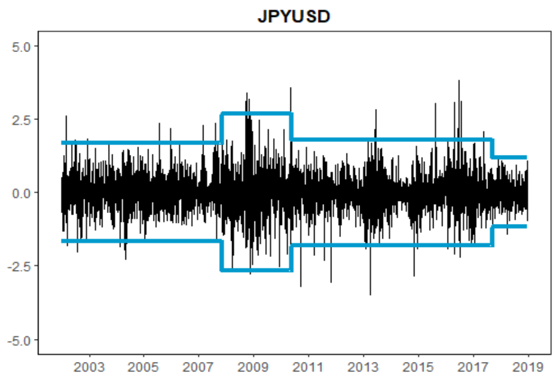

Figure 3 *- Structural Breaks Identified for JPYUSD*

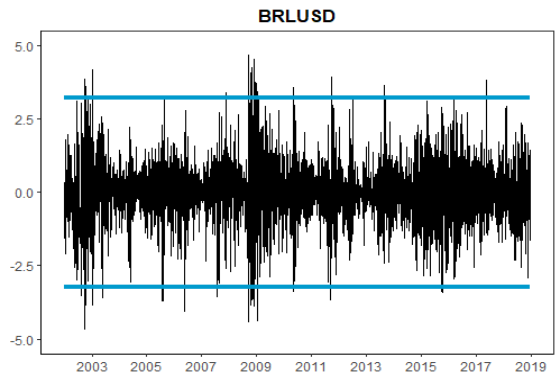

Figure 4 *- Structural Breaks Identified for BRLUSD*

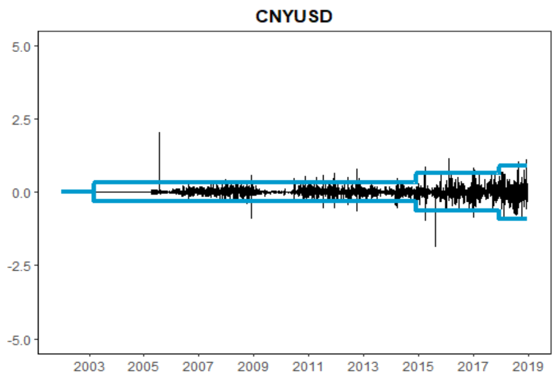

Figure 5 *- Structural Breaks Identified for CNYUSD*

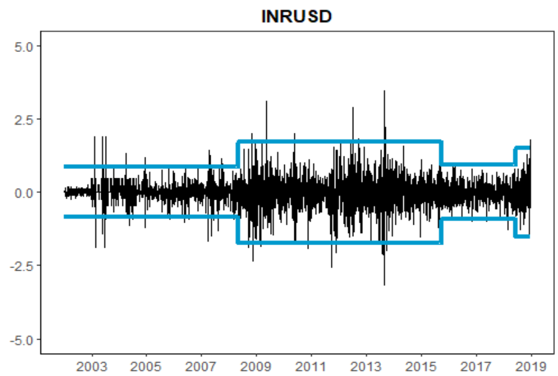

Figure 6 *- Structural Breaks Identified for INRUSD*

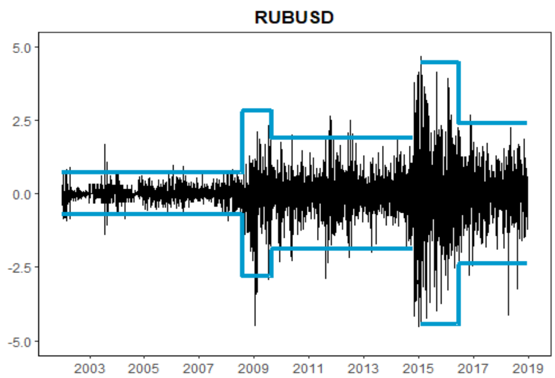

Figure 7 *- Structural Breaks Identified for RUBUSD*

As expected, a significant amount of the breaks identified by the ICSS algorithm throughout the several series in analysis seem to occur in the late ‘00s period, namely 2007 up to 2010. This period was characterized by two very significant phenomena (i) the financial crisis triggered by the subprime loans in the US housing market (ii) a meteoric spike in volatility mainly in the oil sub-category. These events, due to their magnitude and global reach are in our view the main determinants - both directly and indirectly - of the turmoil in which the financial markets sank at the time.

From one side, the worldwide economy was buffeted by the devastating effects of the crisis that emerged in the subprime sector of the US housing markets due to an inappropriate credit scoring, risk management and compliance functions applied by the financial institutions, combined with an insufficient regulatory framework, which, due to an increased amount of defaults in housing mortgage payments, went bankrupt or required a significant federal capital injection to stay afloat. In a globalized and interconnected economic environment, a hit inflicted on the biggest economy will naturally have repercussions on a global scale due (i) to this economy's influence (ii) the diversified range of locations where most of the biggest financial groups operate - thus generating a systemic effect.

On the other, this period is also characterized by immense volatility associated to oil with the Brent being traded at approximately 58 USD/Bbl on January 2007 and just a year and a half later – in June 2008 – reaching a historical maximum of roughly 140 USD/Bbl. Many economies were particularly vulnerable to this prise upswing since they are highly dependent on energy imports to meet and secure their domestic consumption needs - this is particularly true for European economies (part of which are Eurozone members). Just a year and a half later – in January 2009 – the Brent was traded at a value close do 45 USD/Bbl introducing a new abrupt shift in the financial markets.

	EUR	GBP	JPY	BRL	CNY	INR	RBL
Subsample 1	0.297 (0.048)	0.387 (0.083)	0.312 (0.231)	2.017 (1.020)	0.000 (0.000)	0.310 (0.376)	0.501 (0.000)
Subsample 2	0.499 (0.037)		0.757 (0.113)		0.000 (0.000)	0.360 (0.085)	0.908 (0.212)
Subsample 3	0.295 (0.019)		0.395 (0.067)		0.044 (0.003)	0.096 (0.010)	0.400 (0.053)
Subsample 4	0.130 (0.010)		0.158 (0.019)		0.091 (0.010)	0.000 (0.000)	11.709 (2.928)
Subsample 5	0.349 (0.035)						2.210 (0.340)
Subsample 6	1.820 (0.263)						0.634 (0.067)
Subsample 7	0.856 (0.112)						
Subsample 8	0.303 (0.026)						
Subsample 9	0.586 (0.063)						
Subsample 10	0.267 (0.025)						
Subsample 11	0.137 (0.018)						
Subsample 12	0.055 (0.007)						
Subsample 13	0.517 (0.051)						
Subsample 14	0.223 (0.014)						

Table 4 – *Unconditional Variance Estimates Across the Subsamples*

For the eurozone economies in particular, the 2010 - 2015 was a particularly adverse period which is depicted in Figure 1 - as one can see, a significant degree of shifts and structural breaks occurred in the EURUSD series around this time. As a consequence of the global financial crisis in which many governments had to intervene in the economy and bailout its financial institutions, a new problem commenced to emerge: the deterioration of the sovereign financial health and the incurrence in budget deficits in turn led to an abrupt increase in public debt - thus transitioning in a sovereign debt crisis. Eurozone member countries were facing an ever-growing difficulty to secure financing in the international markets - and when they eventually managed to do so, at a high interest rate cost. Now were the European countries that needed to receive bailout packages - European Commission, European Central Bank and the International Monetary Fund - and were required to in return implement a series of emergency economic measures in order to reduce their budget deficits and improve their public debt to GDP ratios. These austerity programs led to a cut in public spending, freezing wages, significative direct and indirect tax increases and to a rocket high unemployment rates in several countries which in turn resulted in a social unrest and political instability in countries such as France, Italy, Portugal and Greece.

As one can see in Figure 3, there is a decrease in the amplitude of the oscillation for the JPYUSD series after the occurrence of the last break in beginning of 2018. Being Japan the main NATO's partner country in the region and standing at the forefront of the several conflicts that involved North Korea over the last decades, the volatile behaviour of its Korean neighbour poses a non-neglectable effect on Japanese national defence and economy. The last quarter of 2017 was particularly unstable in the region with consecutive launches of intermediate range Hwasong-12 ballistic missiles which overflew Japan- in August and September 2017; the successful deployment of the first Korean intercontinental ballistic missile; and the claim by the Korean leader of the successful completion and deployment of a hydrogen bomb. As response, the US, Japan and South Korea increased their trilateral cooperation and even more severe sanctions were imposed on Korea – with it being designated as a *state sponsor of terrorism* and the resolution by the US Security Council which cut almost entirely the refined petroleum received by Korea.

This volatile situation would suffer a significant shift through 2018, with representatives from both Koreas meeting in the demilitarized zone, North Korea sending a delegation to the 2018 Winter Olympics in South Korea, and the reopening of the military hotline between both countries. Several meetings followed between heads of state with the US President meeting the Japanese Prime Minister and the Chinese President meeting the Korean Leader. It's around this point in time that the last break in the JPYUSD series occurs - which we believe was caused by the abrupt shift in events - with the fluctuation after this occurrence depicting a more stable behaviour which can be explained by the normalization of diplomatic relations in the months that followed, with meetings between North and South Korean leaders in the demilitarized zone; the release of American detainees; the meeting in Singapore between the American President and the North Korean Leader and a compromise from North Korea to dismantle it missile launch facilities – all of which have an impact on the Japanese national security and economy.

Most of the breaks identified for the RUB correspond to the 2015 – 2016 period. In the aftermath of the invasion of Ukraine by Russia and subsequent war in Donbass and annexation of Crimea by the Russian Federation, the latter was subject to the imposition of economic sanctions by the international community which restrained economic activity. At the same time, and after a period of relative stability, the commodity international markets were once again in turmoil with the further decline in oil prices which in the mid-2014 was being traded at roughly 112 USD/Bbl down to 35 USD/Bbl in 2016. Being Russia one of the main producers and exporters of oil worldwide, and consequently highly dependent and exposed to the evolution of its price in the international markets, a big hit was inflicted to its economy with the oil's abrupt loss in value. The impact of these joint shocks drove the Russian economy into a period of deep recession (The World Bank, 2016).

The break identified in March 2003 for the CNYUSD series matches the period corresponding to the peak of the Severe Acute Respiratory Syndrome (SARS) which was first identified in late 2002 and had its hotbed in the Chinese province of Guangdong. This epidemic had significative impact on the Chinese economy mainly on its services sector with the tourism and retail services taking the greatest hit. Research shows that the revenue originated from foreigner tourism in China would be down by 60%. More global economic surveys point that due to the multiplier effect the outbreak caused losses of up to 28 Billion USD to Chinese economy alone, and would lead to a reduction in GDP of 1% to 2% had the outbreak not occurred (Hai et al 2004; Qiu et al 2018).

The structural break identified in early April 2018 and the period of increased volatility that followed - that is portrayed in the fourth subsample in the CNYUSD series – coincides with the announcement and application of tariffs by the United States Government to Chinese imports. Initially these tariffs were applied to steel and aluminium but soon the scope was widened, and a diverse set of goods was included. China retaliated to this protectionist policy by also imposing tariffs on goods imported from the United States, which ultimately led to the emergence of a trade war. Naturally, the financial markets responded to this period of increased market volatility with (i) the shares on the Shenzhen Stock Exchange and Shanghai Stock Exchange losing on average 30% and 20% of its value, respectively (ii) the Yuan ending 2018 close to a double-digit percentage devaluation (Lau, 2019).

In the period comprised between 2016 and 2018 two relevant monetary and fiscal events took place in India: the demonetisation of its currency and the enforcement of a comprehensive goods and services tax.

Regarding the former, the Indian Government implemented a set of measures that intended to improve transparency and accountability in its financial system, contributing to minimize corruption, terror funding and counterfeit currencies circulation. To achieve these goals the Government decided to demonetise its highest value currency notes of Rs. 500 and Rs. 1000 which represented around 90% of the value of total currency in circulation. This had an immediate adverse impact on economic activity since Indian economy is a traditionally cash intensive economy with an estimated 78% of consumer payments being made in cash (Reserve Bank of India, 2017; Shekhar and Deb, 2020).

Likewise, the introduction of the goods and services tax intended to impose a more efficient tax structure in order to increase tax revenue, mitigate economic distortions and promote inner-cohesion and the competitiveness of the economy. To do so, it aimed to reform the current local and state tax system in force, replacing the arbitrarily of local and state taxes through the implementation of a single transparent tax (Shekhar and Deb, 2020)

The variation portrayed in the fourth subsample of Figure 6 seems to depict the implementation of these measures

In Table 4 below we present both, the full-sample QMLE GARCH (1,1) parameter estimates applied to the entire sample of each of the seven exchange rate return series, and the QMLE GARCH (1,1) parameter estimates for each of the subsamples defined by each of the structural breaks identified by the modified ICSS algorithm.

	EUR	GBP	JPY	BRL	CNY	INR	RUB
$\hat{\omega}$	0.001 (0.000)	0.003 (0.001)	0.005 (0.001)	0.0195 (0.004)	0.000 (0.000)	0.002 (0.000)	0.000 (0.000)
$\hat{\alpha}$	0.030 (0.004)	0.055 (0.006)	0.048 (0.007)	0.143 (0.013)	0.088 (0.005)	0.121 (0.012)	0.092 (0.008)
$\hat{\beta}$	0.960 (0.004)	0.937 (0.008)	0.939 (0.008)	0.848 (0.013)	0.910 (0.002)	0.871 (0.011)	0.901 (0.007)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.369 (0.091)	0.387 (0.083)	0.404 (0.048)	2.017 (1.021)	0.000 (0.000)	-0.313 (0.276)	-0.041 (0.000)
Subsample 1	**01/01/2002-19/03/2003**	**01/01/2002-31/12/2018**	**01/01/2002-16/12/2007**	**01/01/2002-31/12/2018**	**01/01/2002-16/03/2003**	**01/01/2002-18/05/2008**	**01/01/2002-22/09/2008**
$\hat{\omega}$	0.010 (0.007)	0.003 (0.001)	0.0132 (0.004)	0.019 (0.004)	0.000 (0.000)	0.003 (0.001)	0.000 (0.000)
$\hat{\alpha}$	0.033 (0.017)	0.055 (0.006)	0.041 (0.011)	0.143 (0.013)	0.100 (0.001)	0.209 (0.026)	0.082 (0.011)
$\hat{\beta}$	0.933 (0.032)	0.937 (0.008)	0.917 (0.019)	0.848 (0.013)	0.800 (0.008)	0.780 (0.022)	0.917 (0.009)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.297 (0.048)	0.387 (0.083)	0.312 (0.231)	2.017 (1.020)	0.000 (0.000)	0.310 (0.376)	0.501 (0.000)
Subsample 2	**20/03/2003-16/09/2004**		**17/12/2007-26/07/2010**		**17/03/2003-24/02/2015**	**19/05/2008-26/08/2015**	**23/09/2008-11/10/2009**
$\hat{\omega}$	0.499 (0.037)		0.032 (0.013)		0.000 (0.000)	0.005 (0.002)	0.034 (0.019)
$\hat{\alpha}$	0		0.065 (0.019)		0.082 (0.003)	0.072 (0.012)	0.052 (0.022)
$\hat{\beta}$	-		0.893 (0.032)		0.914 (0.001)	0.913 (0.015)	0.911 (0.031)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.499 (0.037)		0.757 (0.113)		0.000 (0.000)	0.360 (0.085)	0.908 (0.212)

Subsample 3	**17/09/2004-27/08/2006**	**27/07/2010-27/01/2018**	**25/02/2015-02/04/2018**	**27/08/2015-12/05/2018**	**12/10/2009-04/02/2015**
$\widehat{\omega}$	0.295 (0.019)	0.005 (0.002)	0.019 (0.006)	0.010 (0.005)	0.015 (0.005)
$\hat{\alpha}$	0	0.046 (0.010)	0.104 (0.035)	0.092 (0.032)	0.081 (0.016)
$\hat{\beta}$	-	0.940 (0.013)	0.464 (0.145)	0.799 (0.073)	0.880 (0.023)
$\frac{\widehat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.295 (0.019)	0.395 (0.067)	0.044 (0.003)	0.096 (0.010)	0.400 (0.053)
Subsample 4	**28/08/2006-21/12/2007**	**28/01/2018-31/12/2018**	**03/04/2018-31/12/2018**	**13/05/2018-31/12/2018**	**05/02/2015-17/05/2015**
$\widehat{\omega}$	0.130 (0.010)	0.006 (0.007)	0.057 (0.027)	0.000 (0.000)	11.709 (2.928)
$\hat{\alpha}$	0	0.017 (0.017)	0.149 (0.080)	0.025 (0.025)	0
$\hat{\beta}$	-	0.947 (0.055)	0.225 (0.302)	0.972 (0.022)	-
$\frac{\widehat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.130 (0.010)	0.158 (0.019)	0.091 (0.010)	0.000 (0.000)	11.709 (2.928)
Subsample 5	**22/12/2007-01/11/2008**				**18/05/2015-14/10/2016**
$\widehat{\omega}$	0.349 (0.035)				0.262 (0.158)
$\hat{\alpha}$	0				0.114 (0.045)

$\hat{\beta}$	-	0.767 (0.098)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.349 (0.035)	2.210 (0.340)
Subsample 6	**02/11/2008- 16/02/2009**	**15/10/2016- 31/12/2018**
$\hat{\omega}$	1.820 (0.263)	0.083 (0.039)
$\hat{\alpha}$	0	0.100 (0.031)
$\hat{\beta}$	-	0.769 (0.076)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	1.820 (0.263)	0.634 (0.067)
Subsample 7	**17/02/2009- 20/08/2009**	
$\hat{\omega}$	0.856 (0.112)	
$\hat{\alpha}$	0	
$\hat{\beta}$	-	
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.856 (0.112)	
Subsample 8	**21/08/2009- 30/06/2010**	
$\hat{\omega}$	0.303 (0.026)	

$\hat{\alpha}$	0
$\hat{\beta}$	-
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.303 (0.026)
Subsample 9	**01/07/2010-04/02/2012**
$\hat{\omega}$	0.012 (0.016)
$\hat{\alpha}$	0.008 (0.012)
$\hat{\beta}$	0.971 (0.031)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.586 (0.063)
Subsample 10	**05/02/2012-14/10/2013**
$\hat{\omega}$	0.010 (0.012)
$\hat{\alpha}$	0.011 (0.016)
$\hat{\beta}$	0.951 (0.048)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.267 (0.025)
Subsample 11	**15/10/2013-14/06/2014**

$\hat{\omega}$	0.137 (0.018)
$\hat{\alpha}$	0
$\hat{\beta}$	-
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.137 (0.018)
Subsample 12	**15/06/2014- 10/12/2014**
$\hat{\omega}$	0.055 (0.007)
$\hat{\alpha}$	0
$\hat{\beta}$	-
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.055 (0.007)
Subsample 13	**11/12/2014- 05/04/2016**
$\hat{\omega}$	0.197 (0.147)
$\hat{\alpha}$	0.095 (0.057)
$\hat{\beta}$	0.524 (0.316)
$\frac{\hat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.517 (0.051)

Subsample 14	06/04/2016-31/12/2018
$\widehat{\omega}$	0.223 (0.014)
$\hat{\alpha}$	0
$\hat{\beta}$	-
$\dfrac{\widehat{w}}{(1-\hat{\alpha}-\hat{\beta})}$	0.223 (0.014)

Table 5 **-** *QMLE Estimation Results for GARCH (1,1) Models*

When estimated over the full sample, the fitted GARCH (1,1) model exhibits an overall high degree of persistence – in line with the existing literature - with $\hat{\alpha}+\hat{\beta}$ ranging between 0.987 and 0.998. The currencies that exhibit the most persistent behaviour are the CNY, RUB and INR, with 0.998, 0.993 and 0.992 respectively, indicating the existence of conditional heteroskedasticity.

When applying the GARCH (1,1) models over the subsamples defined by the structural breaks identified in each of the series, we conclude that in the case of the EUR the persistence vanishes from the 2nd up to the 8th subsample, the 11th, 12th and 14th subsamples and in the case of the RUB there is an identical effect in the 4th subsample, and therefore, since $\hat{\alpha}=0$, they are characterized by conditional homoskedasticity.

From the results in Table 4 we can conclude that the existence of the structural breaks across the various subsamples leads to substantial shifts in the intercept term $\widehat{\omega}$ which in turn results in considerable changes in the unconditional variance.

Conclusion

Our study aimed to investigate the existence of structural breaks in exchange rate return data and their empirical relevance. In order to analyse for the existence of structural breaks we employed a modified version of the iterated cumulative sum of squares (ICSS) algorithm originally proposed by Inclán and Tiao (1994) on the daily exchange rate return data from seven currencies vis-à-vis the US Dollar in the period comprised between January 1st 2002 and December 31st 2018. The algorithm found significant evidence of the existence of a grand total of twenty-seven structural breaks among all series in analysis, distributed along five out of the seven currency pairs under our scope: thirteen for the EURUSD; five for the RUBUSD; three for the JPYUSD, CNYUSD and INRUSD; and no breaks were identified for the GBPUSD and BRLUSD pairs. When inspecting the approximate date of occurrence of each of the breaks and the upward or downward shift in volatility that it provoked, we were able to associate the time of their occurrence to significant social, political or economic effects. The fitted full sample and sub-sample GARCH (1,1) models exhibit a high level of persistence with $\hat{\alpha} + \hat{\beta}$ ranging between 0.987 and 0.998, thus indicating that the exchange rate returns are characterised by conditional heteroskedasticity. Based on these results we may conclude that structural breaks are a relevant feature of exchange rate return series and must not be neglected when performing modelling and forecasting exercises.

In future research this study would benefit from an out-of-sample forecasting exercise that would extend and co-substantiate our results by utilizing different GARCH-type models and forecasting for different timeframes in order to investigate which performed best.

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