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Analysis of Exchange Rate Volatility in Peru in the Presence of Structural Breaks

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Abstract: The presence of structural breaks in the analysis of volatility in the financial field has been ignored in research done in Latin America. This paper fills this gap by analyzing the behavior of the dollar exchange rate in Peru by evaluating the impact of structural breaks in volatility forecasting. The return behavior was analyzed for the period 05/01/2010 to 09/30/2021. Econometric analysis was used, which consisted of: (1) use of the modified Iterative Cumulative Sum of Squares (ICSS) algorithm to determine the structural breakpoints; (2) estimation of GARCH Models for the subsamples originated by the identified breakpoints; and (3) comparison of alternative models with the GARCH(1,1) expanding window model for horizons of 1, 20, 60 and 120 days. The ICSS algorithm identified 8 breaks in volatility behavior. The models were compared based on out-of-sample forecast performance. It was determined that the GARCH model that considers structural breaks is only effective for a one-day horizon. Finally, the GARCH(1,1) 0.25 rolling window model provides a better strategy for forecasting the volatility of exchange rate returns in Peru for longer horizons.

Keywords: volatility, GARCH, structural breaks, exchange rate.

秘鲁存在结构性中断时的汇率波动分析

摘要：拉丁美洲的研究忽略了金融领域波动性分析中存在的结构性中断。本文通过评估结构性中断对波动率预测的影响，分析秘鲁的美元汇率行为，填补了这一空白。分析了 2010 年 5 月 1 日至 2021 年 9 月 30 日期间的回报行为。使用计量经济学分析，包括：（1）使用改进的迭代累积平方和算法确定结构断点；(2) 对由已识别断点产生的子样本的广义自回归条件异方差模型的估计；(3) 替代模型与广义自回归条件异方差(1,1)扩展窗口模型的比较，用于 1、20、60 和 120 天的视野。迭代累积平方和算法识别出 8 个波动行为中断。这些模型是根据样本外预测性能进行比较的。已确定考虑结构断裂的广义自回归条件异方差模型仅在一日范围内有效。最后，广义自回归条件异方差(1,1) 0.25 滚动窗口模型为预测秘鲁长期汇率回报的波动性提供了更好的策略。

关键词：波动率，广义自回归条件异方差模型，结构性断裂，汇率。

1. Introduction

The modeling of the exchange rate volatility process gives solidity to the economic policy structure of a nation. It generates bases for the democratic dynamics necessary for developing a system, but due to the heteroscedastic nature of the short-run exchange rate returns. These classic models assume stationarity and homoscedasticity are not the most suitable for modeling it. Nevertheless, such modeling is of great importance in macroeconomic decision-making and, in recent decades, has been the subject of research in the financial market.

The exchange rate frequently exhibits periods of large price swings followed by periods of calm. Lately, a macroeconomic analysis has become an important topic of exchange rate movements [1-3]. The issue of

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exchange rate volatility is widely studied due to its potential influence on inflation, international trade, the degree of competitiveness of the economy's external sector, and its role in investment analysis, securities valuation, risk management, and profitability. [4] showed that exchange rate volatility has a significant effect on export products. In addition, exchange rate prediction is considered important for establishing costs and benefits [5].

The behavior of volatility is mathematically expressed from the GARCH. However, these models do not consider changes in volatility, called structural breaks. That induces large biases, giving rise to poor estimates of volatile processes [6]. Structural breaks are relevant in volatility modeling using GARCH. Their inclusion usually improves out-of-sample volatility forecasts [7].

There are studies concerning the volatility in the Latin American environment without considering the presence of breaks [8]. Another research [9] concluded that exchange rate volatility has a significant impact on the export flows of eight Latin American countries.

In the Latin American environment, few studies on volatility consider the presence of breaks [8]. Research that did not consider breaks concludes that exchange rate depreciation has a greater impact on exchange rate volatility [9].

In Peru, [10] analyzed the IGBVL volatility, concluding that a GARCH(1,1) model best explains the variance behavior. In addition, [11] concludes that the behavior of the exchange rate is generally influenced by information from its previous behavior.

No studies analyze the influence of breaks in volatility, both in Peru and in Latin America. For this reason, the objective of this paper is to examine the temporal variation of the volatility of the U.S. dollar exchange rate in Peru during the period 2010-2021, considering the presence of structural breaks. Furthermore, the period under study is considered because it includes recent events that Peru has experienced, both in the political arena and in the health area, which caused instability in the dollar price in Peru.

2. Materials and Methods

2.1. Data and Variables

This study uses the daily dollar exchange rate in Peru for the period 01/05/2010 to 09/30/2021, with a total of 2,922 data. The data were obtained from the Central Bank of Reserves (BCR) website. Daily dollar exchange rate returns were obtained from the exchange rate. The data were processed using free software such as R version 4.1 and Python version 3.9.

2.2. Econometric Methodology

2.2.1. Modified ICSS Algorithm

If we denote the daily return on the dollar as

$$r_t = 100[ln(P_t) - ln(P_{t-1})],$$

from time $t-1$ to period t, for $t = 1, \dots, T$. P_t denotes the selling price of the dollar at time t and $e_t = r_t - \mu$, where μ is the (unconditional) constant mean of r_t.

For checking structural changes in variance occurring at some point in time, the modified ICSS algorithm was applied [12]. The research [13] provides the ICSS algorithm to determine structural changes in the unconditional variance, but this method is not suitable for dependent processes like GARCH models. In this sense, [12] makes a non-parametric adjustment to the algorithm proposed by [13].

2.2.2. In-Sample Test

The In-Sample Test procedure is divided into two phases:

Phase 1: The modified ICSS algorithm determines structural breaks in the unconditional volatility of the series under study.

Phase 2: We estimate GARCH(1,1) models for the complete series and the subsamples defined from the breakpoints identified in phase 1, allowing us to evaluate their empirical relevance.

We express the GARCH(1,1) model for e_t with zero mean as

$$e_t = \sigma_t \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (2)$$

with $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$. If $\alpha + \beta < 1$, the series e_t has a finite variance and being a martingale in differences, it is white noise, of mean zero and variance $Var(e_t) = \frac{\alpha}{1-\alpha-\beta}$. σ_t^2 represents the conditional volatility of r_t, and ε_t is i.i.d. with mean zero and unit variance. The model coefficients are often estimated using the quasi-maximum likelihood method (QMLE) due to its estimators' consistency and asymptotic normality [14, 15].

2.2.3. Out-of-Sample Test

We analyzed the out-of-sample volatility forecasts by dividing them into two parts: the first R observations constituted the in-sample component, and the last P observations the out-of-sample component, such that T=R+P. We used the GARCH(1,1) expanding window model as the reference model. In addition, to analyze the possible effects coming from structural breaks in the volatility forecast, we used seven forecasting approaches for horizons of 1, 20, 60, and 120 days.

FIGARCH(1,d,1) represents the slow decay of the autocorrelations of the squared returns allowing a significant improvement in their prediction for a long memory process. The model is expressed as

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + [1 - \mathrm{B}\mathrm{L} - (1 - \phi \mathrm{L}) \mathrm{z}_t^2 \quad (3)$$

where L is the lag operator.

GARCH(1,1) 0.5 rolling window uses a rolling estimation window equal to half the size of the period in the sample to make the forecast.

GARCH (1,1) 0.25 rolling window uses a moving estimation window equal to one-fourth of the in-sample period size.

GARCH(1,1) expanding window using weighted maximum likelihood estimators. This model handles the structural instability that can appear in GARCH parameters very well.

GARCH(1,1) takes into account the presence of structural breakpoints.

Moving Average using the Average of the squared returns over the previous 300 days to forecast volatility on day t. At longer horizons, the moving average model can improve the daily volatility forecast compared to GARCH(1,1) models, even more so in the presence of structural breaks.

GJR-GARCH(1,1) expanding window is used to capture the effect of leverage.

We use a loss function to compare volatility forecasts between the different models used. The aggregate version of the proposed metric is the mean squared forecast error (MSFE) which is given by

$$MSFE_{S,1} = [P-(S-1)]^{-1} \sum_{t=R+2}^{T} (\tilde{e}_t^2 - \tilde{\hat{\sigma}}^2_{t|t-s,1})^2 \quad (4)$$

where

$$\tilde{e}_t^2 = \sum_{j=1}^{s} e^2_{t-(j-1)} \text{ y } \tilde{\hat{\sigma}}^2_{t|t-s,i} = \sum_{j=1}^{s} \sigma^2_{t-(j-1)} \mid t-s, i. \quad (5)$$

Significant differences in MSFE between the reference model and a competition model were tested using the statistic developed by [16]. This statistic allows us to establish significant differences in the forecasts of nested models. Therefore, the competing models in this research are considered nested models.

3. Results

3.1. Data and Descriptive Statistics

We analyzed the behavior of the daily return of the dollar in Peru in the period 05/01/2010 to 09/30/2021. Descriptive statistics are reported in Table 1. We use the closing prices to calculate the daily dollar returns. The mean return is 0.0123 with a standard deviation of 0.2935.

An excess Kurtosis (14.2293) also indicates a leptokurtic distribution, which is an apparent deviation from normality. The daily stock returns appear very volatile. Furthermore, the presence of serial correlations in the squared returns and the confirmation of ARCH effects ($p < 0.01$) support the use of GARCH models to describe the behavior of the volatility of dollar price returns in Peru.

Table 1 Summary statistics of exchange rate returns

	Returns	**p-value**
Return Average	0.0123	
Standard Deviation	0.2935	
Asymmetry	-0.2480	
Kurtosis	14.2293	
Minimum	-2.9638	
Maximum	3.0123	
Square Exchange Rate Return Ljung-Box (r = 20)	486.6821	0.000
ARCH LM (q = 2)	200.7360	0.000
ARCH LM (q = 10)	278.446	0.000

Fig. 1 shows the ups and downs in the exchange rate during the sample period. It shows periods in which large changes are followed by other large changes and periods in which other small changes follow small changes. In addition, the significant point to note is that volatility occurs in clusters.

Periods of relative tranquility are seen, especially between 2014 - 2015 and 2017 - 2019, during which small positive and negative returns were present. On the other hand, during the years 2016, 2020, and part of 2021, there was greater volatility, observing positive and negative returns of greater magnitude. This previous analysis concludes that volatility is autocorrelated [17].

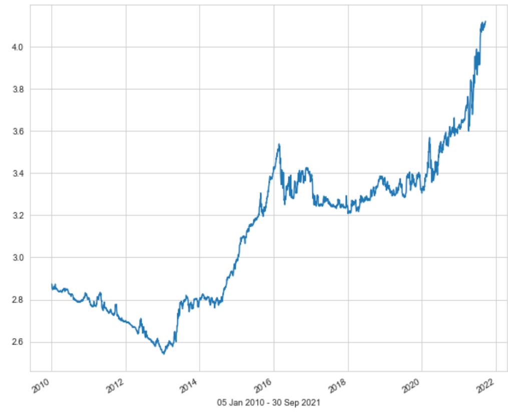

Fig. 1 Dollar selling price

3.2. In-Sample Results

Table 2 shows the eight break points in conditional volatility. The breakpoints are also presented in Fig. 2 and were found using the modified ICSS algorithm.

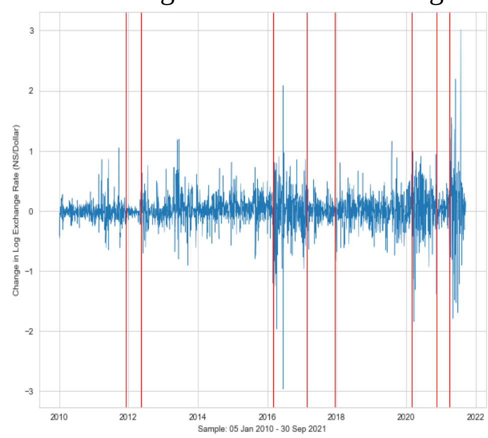

Fig. 2 Structural breakpoints

Table 3 shows the estimated coefficients of the GARCH(1,1) models for the total sample period and the subsamples. For the total sample, in the fitted GARCH(1,1) model, we find that $\alpha + \beta \approx 0.999$ indicates a high volatility persistence. The subsamples GARCH(1,1) models, except for subsamples 2, 6, and 8, present estimates of $\alpha + \beta > 0.95$ indicating high persistence and characterizing them by conditional heteroscedasticity. According to [7], these changes in the persistence of the volatility process may be due to not considering structural breaks.

In addition, the unconditional variance presented significant changes, which are reflected by the values of de $\omega/(1-\alpha-\beta)$. These changes are due to breakpoints that cause a significant change in ω. In addition, the values of the estimated coefficients of the GARCH(1,1) model vary between the subsamples. Overall, the results indicate that the conditional variance of exchange rate returns is highly persistent and that structural breaks characterize them significantly.

Table 2 Structural breaks in volatility with a time period

Sample	Structural breaks	Time Period
Total Sample	8	05/01/2010 - 20/09/2021
Subsample 1		05/01/2010 - 01/12/2011
Subsample 2		02/12/2011 - 11/05/2012
Subsample 3		11/05/2012 - 01/03/2016
Subsample 4		02/03/2016 - 21/02/2017
Subsample 5		22/02/2017 - 14/12/2017
Subsample 6		15/12/2017 - 27/02/2020
Subsample 7		28/02/2020 - 19/11/2020
Subsample 8		20/11/2020 - 05/04/2021
Subsample 9		05/04/2021 - 30/09/2021

Table 3 QMLE estimation results for GARCH models (1,1)

	Total Sample	Subsample 1	Subsample 2	Subsample 3
ω	0.001 (0.00)	0.001 (0.001)	0.002 (0.009)	0.003 (0.001)
α	0.234 (0.04)	0.672 (0.23)	0.835 (0.46)	0.162 (0.05)
β	0.765 (0.04)	0.321 (0.13)	0.005 (0.33)	0.776 (0.06)
$\frac{\omega}{1-\alpha-\beta}$	1.56	0.06	0.012	0.05
	Subsample 4	**Subsample 5**	**Subsample 6**	**Subsample 7**
ω	0.020 (0.01)	0.003 (0.002)	0.015 (0.008)	0.009 (0.01)
α	0.409 (0.14)	0.201 (0.10)	0.224 (0.10)	0.190 (0.18)
β	0.556 (0.08)	0.714 (0.010)	0.525 (0.18)	0.783 (0.12)
$\frac{\omega}{1-\alpha-\beta}$	0.57	0.03	0.06	0.33
	Subsample 8	**Subsample 9**		
ω	0.010 (0.01)	0.000 (0.01)		
α	0.205 (0.19)	0.110 (0.07)		
β	0.434 (0.19)	0.889 (0.07)		
$\frac{\omega}{1-\alpha-\beta}$	0.028	0.00		

3.3. Out-of-Sample Results

We consider the last 300 observations of the entire sample period and cover the period from July 23, 2020, to September 30, 2021, including the last two structural breaks. Table 4 presents the out-of-sample volatility forecast results for the different horizons. The MSFE for each forecasting method and its comparison ratio with the MSFE of the GARCH(1,1) expanding window model are presented. A model with a ratio less than unity performs better than the model in reference. The test developed by [15] was applied to determine whether the competing model, compared to the GARCH(1,1) expanding window model, had a lower expected loss.

We compared the GARCH(1,1) expanding window model in the first two rows of each horizon and the FIGARCH(1,d,1) model. The benchmark model performs better at horizons s = 1 and 20, and the FIGARCH model performs better at horizons s = 60 y 120, indicating that this model is suitable for long memory processes.

On the other hand, the GARCH(1,1) model with breaks shows a lower average loss rate at the 1-day horizon than the benchmark and competing models. However, its performance worsens at higher forecast horizons, although it performs relatively better than the GJR-GARCH(1,1) expanding window and moving average models. At the 60 and 120-day horizons, the GARCH(1,1) 0.25 rolling window model performs better than the benchmark model. Moreover, as mentioned above, the GARCH(1,1) model with breaks cannot outperform the benchmark model. These results allow us to conclude that it is not easy to determine an estimation window that would allow us to make more accurate volatility forecasts from a GARCH(1,1) model. Weighted maximum likelihood and moving average GARCH(1,1) models never offer volatility forecast gain related to the benchmark.

Table 4 Out-of-sample prediction results

	s = 1		s = 20	
	MSFE	**Ratio**	**MSFE**	**Ratio**
GARCH(1,1) expanding window	2.50	1.00	61.98	1.00
FIGARCH expanding window	2.65	1.06	102.34	1.65
GARCH(1,1) 0.50 rolling window	4.70	1.88	164.24	2.65

Continuation of Table 4				
GARCH(1,1) 0.25 rolling window	6.33	2.53	182.73	2.95
GARCH(1,1) MV weighted	6.56	2.62	185.44	2.99
GARCH(1,1) with breaks	2.39	0.96*	63.31	1.02
Moving Average	3.17	1.27	199.22	3.21
GJR-GARCH(1,1) expanding window	4.48	1.79	55.07	0.89*
	s = 60		**s = 120**	
	MSFE	**Ratio**	**MSFE**	**Ratio**
GARCH(1,1) expanding window	536.90	1.00	2583.68	1.00
FIGARCH expanding window	514.66	0.96	2161.92	0.84
GARCH(1,1) 0.50 rolling window	1026.47	1.91	3162.20	1.22
GARCH(1,1) 0.25 rolling window	415.32	0.77*	2002.51	0.77*
GARCH(1,1) MV weighted	581.92	1.08	3302.74	1.28
GARCH(1,1) with breaks	557.41	1.07	2830.25	1.09
Moving Average	1075.23	2.00	3102.23	1.20
GJR-GARCH(1,1) expanding window	1070.11	1.99	3967.76	1.54

* Significant ratio at $p < 0.05$

4. Discussion

A proper analysis of volatility in financial series, such as stock market shares and the exchange rate, is crucial in macroeconomic decision-making. Its accurate modeling allows for establishing a sound economic policy of a country [17]. However, this volatile behavior of financial series is not constant over time and usually presents changes in the mathematical structure that tries to explain its behavior.

Much research on forecasting exchange rate volatility, but unfortunately, the presence of structural breaks has not been considered in previous research on exchange rate volatility in Latin America, especially in Peru. [11] did not consider the presence of structural breaks, assuming a stable GARCH process.

The present paper shows that the GARCH(1,1) 0.25 rolling window model for longer horizons shows a significant gain. However, as expressed by [17], the optimal size of the estimation window used in the prediction model is related to the rupture's size, moment, and direction, which makes its selection difficult.

5. Conclusions

Although GARCH models are frequently used in volatility forecasting, little attention has been paid to the impact of structural breaks on such forecasts. Research assumes the existence of a stable volatility process. It, therefore, uses a recursive (expanding) or fixed window size when estimating the GARCH model used to generate out-of-sample volatility forecasts. If there is a structural break in the volatility pattern, the model's volatility forecast may no longer be consistent or reliable without considering the structural break. As a result, GARCH models do not accurately track changes in unconditional variance, resulting in forecasts that underestimate or overestimate volatility over long periods. To this, we add that in Latin America, there are no studies that consider the presence of structural breaks in the analysis of volatility.

Our study differs in several aspects from previous studies in Latin America. First, we consider the presence of structural breaks in volatility analysis by applying an econometric methodology that allows us to identify them and not consider a stable GARCH process in volatility forecasting. Second, it focuses on an important emerging market in Latin America: Peru, for which the existing literature indicates a gap in this type of analysis. Finally, we used the modified ICSS algorithm to identify breakpoints and estimated GARCH models for each identified subsample. That allowed us to combine forecasts of estimated volatility models and use different window sizes, which provides a better strategy for forecasting exchange rate volatility.

The results show the relevance of structural breaks in the GARCH models when explaining the volatility behavior of the U.S. dollar exchange rate performance in Peru. Applying the modified ICSS algorithm in the sample found eight structural breaks in the GARCH(1,1) processes, resulting in significant changes in the GARCH(1,1) parameter estimates across subsamples.

Using an out-of-sample period from July 23, 2020, to September 30, 2021, for Peru, including the last two structural breaks, we find the GARCH(1,1) model with structural breaks only shows a significant gain in predictive ability compared to the benchmark GARCH(1,1). That expands the window model at a horizon equal to one. The GJR-GARCH(1,1) expanding window model, estimated to capture the effects of leverage, showed a significant gain in success at a horizon equal to 20. On the other hand, the GARCH(1,1) 0.25 rolling window model shows significant gain at horizons equal to 60 and 120.

In addition, the combination of forecasting models using different windows provides a better strategy for forecasting the volatility of exchange rate returns in Peru.

The study is one of the first to evidence the presence of structural breaks in the volatile behavior of an economic variable in Latin America, especially in Peru. Therefore, we hope that regulators and financial policymakers will consider this study for the creation of policies that support the stock market. That is because the exchange rate is an important factor that investors should consider before investing in stocks.

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