The Impacts of Monetary Policy Announcements and Derivatives Maturity on the Mexican Peso Exchange Rate Volatility: GARCH and OHLC Range Models

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Lecturas de Economía - No. 103. Medellín, enero-junio 2025

Lecturas de Economía, 103 (enero-junio 2025), pp. 47-75

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Abstract: *We analyze the impact of interest rate changes and derivatives maturity announcements on exchange rate volatility in Mexico. To do so, we first estimate volatility using four measures of range volatility (OHLC models) and three extensions of the GARCH family (GARCH, TARCH and EGARCH), assuming normal distribution, t-Student and GED. Once volatilities are estimated, the impact of monetary policy announcements and derivatives maturity on the MexDer is estimated using daily closing, opening, high, and low data during the period January/2013-April/2024. The results show that range volatility measures underestimate exchange rate volatility. Apparently, derivatives maturities and monetary policy announcements have a negative effect on range/intraday volatilities, but not on the conditional volatility that contemplates persistence and asymmetry in volatility.*

Keywords: *maturity of derivatives, monetary policy decisions, foreign exchange volatility, GARCH models, range models.*

JEL Classification: G11, F31, G13, G15

Impactos de los Anuncios de Política Monetaria y del Vencimiento de Derivados sobre la Volatilidad del Tipo de Cambio del Peso Mexicano: Modelos GARCH y OHLC Range

Resumen: *El presente artículo tiene por objetivo analizar el impacto de los anuncios de cambios de tasas de interés y del vencimiento de los derivados en la volatilidad cambiaria en México. Para ello, primero se estima la volatilidad mediante cuatro medidas de volatilidad de rango (modelos OHLC) y tres extensiones de la familia GARCH (GARCH, TARCH y EGARCH) asumiendo distribución normal, t-Student y GED. Una vez estimadas las volatilidades, se estima el impacto de los anuncios de política monetaria y del vencimiento de derivados en el MexDer. Se emplean datos diarios de cierre, apertura, máximo y mínimo durante el periodo 2013-Mayo/2024. Los resultados arrojan que las medidas de volatilidad de rango infravaloran la volatilidad cambiaria. Aparentemente, los vencimientos de los derivados y los anuncios de la política monetaria tienen un efecto negativo en las volatilidades de rango/intradía, pero no en la volatilidad condicional que contempla persistencia y asimetría en la volatilidad.*

Palabras clave: *vencimiento de derivados, decisiones de política monetaria, volatilidad cambiaria, GARCH, modelos de rango.*

https://doi.org/10.17533/udea.le.n103a358443

Annonces de politique monétaire et maturité des produits dérivés. Impacts sur la volatilité du taux de change du peso mexicain : Modèles GARCH et OHLC

Résumé: *maturité des produits dérivés, décisions de politique monétaire, volatilité des taux de change, GARCH, modèles à fourchettes. L'objectif de cet article est d'analyser l'impact des annonces de taux d'intérêt et d'échéances de produits dérivés sur la volatilité du taux de change au Mexique. Pour ce faire, nous estimons d'abord la volatilité en utilisant quatre mesures de volatilité de rang (modèles OHLC) et trois extensions de la famille GARCH (GARCH, TARCH et EGARCH) en supposant une distribution normale, t-Student et GED. Une fois les volatilités estimées, l'impact des annonces de politique monétaire et de la maturité des produits dérivés sur le MexDer est estimé en utilisant les données quotidiennes de clôture, d'ouverture, de haut et de bas sur la période 2013-mai/2024. Les résultats montrent que les mesures de volatilité de la fourchette sous-estiment la volatilité du taux de change. Apparemment, les échéances des produits dérivés et les annonces de politique monétaire ont un effet négatif sur les volatilités de la fourchette/intraday, mais pas sur la volatilité conditionnelle qui capture la persistance et l'asymétrie de la volatilité*

Mots clés: *maturité des produits dérivés, décisions de politique monétaire, volatilité des taux de change, GARCH, modèles à fourchettes.*

Cómo citar / How to cite this item:

Sosa-Castro, M. M., Cabello-Rosales, M. A., & Ortiz-Calisto, E. (2025). Monetary Policy Announcements and Derivatives Maturity Impacts on Mexican Peso Exchange Rate Volatility: GARCH and OHLC Range Models. *Lecturas de Economía*, *103*, 47-75.
https://doi.org/10.17533/udea.le.n103a358443

The Impacts of Monetary Policy Announcements and Derivatives Maturity on the Mexican Peso Exchange Rate Volatility: GARCH and OHLC Range Models

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–Introduction. –I. Literature Review. –II. Data and Methodology. –III. Results. –Conclusion. –Acknowledgment. –Ethics Statement. –References.

Original manuscript received on 23 March 2024; final version accepted on 19 February 2025

Introduction

Exchange rate volatility is crucial in the current financial context, especially for developing countries, due to its direct impact on economic stability, inflation, and international competitiveness (Olamide *et al.*, 2022). In 2022, several developing countries faced significant exchange rate volatility, which triggered inflationary pressures and undermined domestic economic stability.

In Turkey, for example, the rapid depreciation of the lira eroded purchasing power and forced policymakers to resort to unconventional monetary measures. In Argentina, the peso plummeted alongside soaring inflation, exacerbating government debt burdens and stifling business growth. Meanwhile, Sri Lanka's swift rupee devaluation led to a sharp decline in foreign reserves, curtailing vital imports and sparking social unrest.

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These cases illustrate how abrupt exchange rate swings can destabilize developing economies, complicate government financing efforts, and amplify inflationary pressures, ultimately requiring urgent policy interventions to stave off broader economic and social consequences.

As illustrated above, abrupt exchange rate fluctuations can create market uncertainty, making financial planning challenging for both governments and businesses. In developing countries, where economies are often more vulnerable and dependent on foreign investment and commodity exports, this volatility can discourage investment, increase the cost of external debt, and trigger currency crises (Yabu & Kimolo, 2020). Moreover, exchange rate changes can affect the prices of imported goods, impacting inflation and the purchasing power of the population, further complicating the economic and social management of these countries (Esquivel & Larrain, 2002).

Monetary policy announcements can significantly impact exchange rate volatility because they signal changes in interest rates, money supply, and other economic indicators that influence investor expectations and behavior (May *et al.*, 2018). When a central bank announces a policy shift, such as raising or lowering interest rates, it affects the return on investments denominated in that currency, prompting investors to reallocate their portfolios (Ogundipe, *et al.*, 2019). This can lead to rapid inflows or outflows of capital, causing sudden changes in the demand and supply of the currency and, consequently, its exchange rate. Additionally, the uncertainty surrounding the timing and magnitude of policy changes can heighten market speculation, further amplifying exchange rate fluctuations. In this way, monetary policy announcements play a crucial role in shaping currency market dynamics and volatility (Demirer, *et al.,* 2021).

Derivatives maturities can impact exchange rate volatility by triggering large-scale adjustments in the positions of market participants as contracts approach expiration. When derivatives like futures or options contracts on currencies near their maturity date, investors and institutions must settle their positions, either by delivering the underlying asset or by rolling over to new contracts. This can lead to significant buying or selling pressure on the currency, creating abrupt shifts in its supply and demand. Additionally, the concentration of contract expirations around specific dates can lead to clustering of market activities, intensifying short-term volatility. The strategic maneuvers by investors to manage their exposure and the potential unwinding of speculative positions can further exacerbate these fluctuations, making derivatives maturities a key factor in exchange rate volatility. According to Liao and Zhang (2021), this phenomenon is consistent with the hedging channel of exchange rate determination.

Based on the previously mentioned, this paper examines how monetary policy announcements and derivatives maturities impact exchange rate volatility, measured by different approaches: intraday (OHLC) and conditional volatility, and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The hypothesis is that both events have an impact on exchange rate volatility.

Testing the impact of derivatives maturities and monetary policy announcements on exchange rate volatility is important for understanding the underlying drivers of market fluctuations and enhancing financial stability. By identifying the extent and nature of these impacts, policymakers, investors, and financial institutions can better anticipate and manage potential risks associated with sudden exchange rate movements. This knowledge can inform the design of more effective monetary policies and regulatory frameworks, helping to mitigate adverse effects on economies, particularly in developing countries where exchange rate volatility can have more pronounced economic and social consequences. Additionally, it can aid investors in developing strategies to protect their portfolios from unexpected market disruptions.

Measuring volatility using technical analysis measures, including open, close, high, and low prices, offers several advantages. These measures provide a comprehensive view of price fluctuations within a given period, capturing intraday movements that might be missed by other volatility metrics (Mallqui & Fernandes, 2019). This approach helps traders and analysts identify trends, potential reversals, and periods of increased risk more accurately. Additionally, these measures are easily accessible and can be applied to various time frames, making them versatile for different trading strategies and investment horizons. Overall, technical analysis-based volatility measures enhance decision-making by providing real-time insights into market behavior (Calderón & Kubota, 2018).

On the other hand, measuring volatility based on GARCH models offers several advantages. GARCH models effectively capture the clustering of volatility, where high-volatility periods tend to follow high-volatility periods and low-volatility periods follow low-volatility periods, a common phenomenon in financial markets (Ruslan & Mokhtar, 2021). This dynamic approach allows for more accurate and responsive volatility forecasting compared to static models. GARCH models can also incorporate historical data and account for the persistence of shocks over time, providing a more nuanced understanding of volatility patterns (Khan, *et al.* 2023). Additionally, they can deal with asymmetries and leverage effects, whereby negative shocks may impact volatility differently than positive ones. Overall, GARCH models enhance risk management, pricing of financial instruments, and strategic decision-making by providing a sophisticated and realistic assessment of market volatility (Guo, 2022).

The remainder of the paper is as follows: Section I reviews pertinent literature, Section II describes the methodology, Section III presents empirical evidence, and Section IV concludes.

I. Literature Review

Exchange rate volatility is the subject of extensive research since it significantly influences international trade (Sugiharti *et al.*, 2020), investment, and economic stability (Morina, *et al.* 2020; Nor *et al.*, 2020). Volatile exchange rates can create uncertainty, affecting the cost of cross-border transactions and the profitability of international investments (Fasanya *et al.*, 2021; Kostika & Laopodis, 2020). This volatility also poses challenges for businesses and investors in managing financial risks, prompting the need for effective hedging strategies (Cho, Min & McDonald, 2020; Iyke *et al.*, 2022). Moreover, understanding exchange rate dynamics is crucial for policymakers to formulate appropriate monetary and fiscal policies that ensure macroeconomic stability (Bianchi *et al.*, 2021; Itskhoki & Mukhin, 2023). Consequently, the intricate and far-reaching impact of exchange rate movements on the global economy drives ongoing research in this area.

Exchange rate volatility modeling has been the subject of several academic publications. Escobar (2024) analyzes exchange rate volatility in Costa Rica, Guatemala, Honduras, and the Dominican Republic from 2016 to 2023, using ARCH and GARCH models. The results suggest that each currency has unique dynamics in response to local and global shocks, such as the pandemic, which elicited a coordinated, explosive response from all markets in March 2020. The author finds that the 2024 US presidential election results will influence remittance uncertainty. In this case, exchange rate volatility could increase, so local authorities should be prepared.

Naimy *et al.* (2021) model exchange rate volatility of the six major cryptocurrencies and world currencies. They employ GARCH models (SGARCH, IGARCH, EGARCH, GJRGARCH, APARCH, TGARCH and CGARCH) from 2015 to 2019. The findings reveal the in-sample and out-of-sample superiority of the IGARCH model in terms of world currency forecasting. In the case of cryptocurrencies, GARCH advanced models are more effective at capturing asymmetries and other stylized effects.

Dinga *et al.* (2023) utilize univariate time series analysis to model and forecast the volatility of exchange rates between Cameroon's FCFA (XAF) and the US Dollar (USD), as well as between the FCFA and the Chinese Yuan (CNY). By analyzing daily closing prices from January 1, 2017, to September 30, 2022, the research employs both symmetric Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models and asymmetric models, including Exponential GARCH (EGARCH) and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), to capture the characteristic patterns of exchange rate returns. Leverage effects are observed in the CNY/XAF exchange rate but are not present in the USD/XAF exchange rate data. The findings indicate that conditional heteroscedastic models are effective in modeling and forecasting the conditional volatility of exchange rate series.

Darie and Tache (2022) employ a symmetric GARCH model, specifically GARCH (1,1), to estimate the TRY/USD (Turkish Lira/US dollar) exchange rate with data spanning from January 2014 to October 2019. The study demonstrates that GARCH (1,1) is effective in modeling and predicting the volatility trends of currencies, making it useful for exchange rate management.

Furthermore, research often includes open, close, high, and low prices to estimate exchange rate volatility, as these data points provide a comprehensive perspective on the market's daily fluctuations. Open and close prices represent the initial and final values of a trading day, while high and low prices capture the extreme values within that period. Together, these four prices encapsulate the range and direction of price movements, offering detailed insights into the market's behavior and sentiment. This granularity helps improve the accuracy of volatility models by capturing the full extent of daily price variability, which is essential for robust risk management, trading strategies, and economic analysis.

Sheraz *et al.* (2022) study the presence of long memory and bidirectional information flow in the volatilities of five cryptocurrencies. They use the Garman and Klass (GK), Parkinson's, Rogers and Satchell (RS), Garman and Klass-Yang and Zhang (GK-YZ), and Open-High-Low-Close (OHLC) volatility estimators to measure the volatilities of these cryptocurrencies. The results confirm the long-term dependence and non-linear behavior in the log returns and volatilities of all cryptocurrencies.

Ari (2022) models the volatility of the USD/TRY (Turkish lira), comparing range-based (OHLC) and return-based volatility models. Specifically, Conditional Autoregressive Rank (CARR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models with various distributions are evaluated, as well as the Exponential Weighted Moving Average (EWMA) model with both fixed and estimated lambda parameters. The results reveal that the CARR Exponential and CARR Weibull statistics are the most accurate in explaining currency volatility.

In close connection to this research, Kuncoro (2020) examines whether the interest rate policy in inflation-targeting frameworks may reduce the volatility of exchange rates. The study spans from 2005 (7) to 2016 (7). An ARDL model is employed, and the findings suggest that interest rate policy and foreign exchange intervention are ineffective at reducing exchange rate volatility.

Keefe (2020) studies the impact of monetary policy shocks on exchange rate volatility in Nigeria from 2009 to 2019, employing the VEC model and the impulse response function to forecast error variance decomposition. The findings show that in the long run, there is a significant correlation between monetary policy and exchange rate volatility.

The relationship between the derivatives market and other markets has also been the subject of research. Bernal-Ponce *et al.* (2020) analyze the impact of derivatives on the relationship between the exchange rate and the stock market in Brazil and Mexico from 2007 to 2019 by employing a GMM model. Evidence revealed that exchange rate futures explain the spot exchange rate and currency exposure, where the derivative effect is most pronounced.

Singh and Patra (2022) employ the GARCH (1,1) model to investigate the impact of introducing exchange rate futures on exchange rate volatility for various currencies (USD/INR, EURO/INR, GBP/INR and JPY/INR). The results suggest that volatility diminished after the futures market introduction.

Based on the previous research, we extend the literature by testing whether the monetary policy announcements and Futures and Options Maturities traded in MexDer (Mexican Derivatives Market) impact exchange rate volatility, as measured by OHLC and GARCH volatilities.

II. Data and Methodology

A. Data

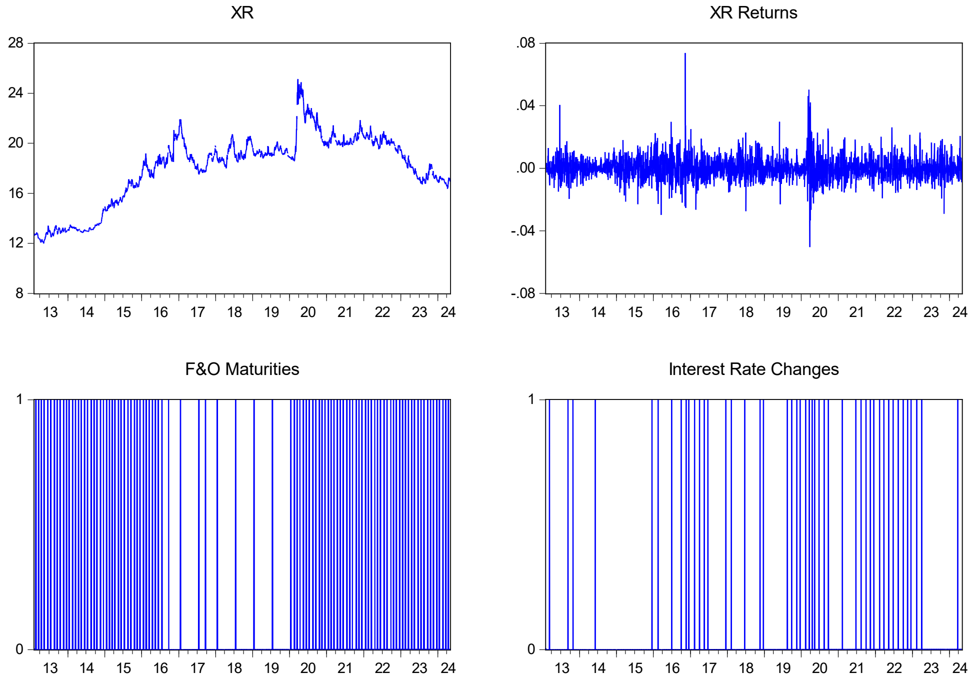
We employ exchange rate MXN/USD data from 01/2013 to 04/2024. The exchange rate series and information about Monetary Policy Announcements were obtained from Mexico's Central Bank (Banco de Mexico, n.d.) website. Futures and options maturities data were downloaded from the MexDer website. Figure 1 shows the evolution of exchange rate levels and returns, interest rate changes, and futures and options maturities[1].

As shown in Figure 1, the Mexican peso depreciated from 2013 to early 2017. This was followed by a period of relative stability until the beginning

[1] For derivatives maturities, the data considered was from the last trading day to the expiration date, to contemplate roll-over effect.

of 2020. The currency experienced an abrupt depreciation in response to the COVID-19 pandemic, but it subsequently recovered to $16.33 MXN/USD. In terms of returns, the largest variations are observed in June 2013, attributed to negative economic growth forecasts: in November 2016, following Donald Trump's election as US president; and in March 2020, due to the pandemic declaration.

Figure 1. *Data: Exchange rate (XR), exchange rate returns, F&O Maturities, and Interest Rate changes*



Source: Own elaboration with estimation results.

The derivatives market appears to be aligned with uncertainty in the FOREX market during the periods when more futures and options contracts were offered, specifically from 2013 to 2016 and from 2020 to 2024. The largest number of interest rate changes occurred from 2015 to 2017, as well as during pre- and post-pandemic periods.

B. Methodology: Volatility Models

B.1 GARCH models

GARCH, EGARCH, and TGARCH are effective methodologies for modeling exchange rate volatility due to their ability to capture and analyze the complexities and nuances of financial time series data.

B.2 GARCH- type models employed

GARCH $h_t^2 = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}^2$

EGARCH $\log\left(h_t^2\right) = \omega + \alpha\left[\left|\frac{u_{t-1}}{h_{t-1}}\right| - \sqrt{2/\pi}\right] + \beta\log\left(h_{t-1}^2\right) + \delta\frac{u_{t-1}}{h_{t-1}}$

TARCH $h_t^2 = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$

where h_t^2 is the conditional variance of u_t, and ω is a permanent component of h_t^2. All the GARCH specifications are considered with innovations distributed as follows: Normal (Gauss), t-Student, and Generalized Error Distribution (GED).

Nelson (1991) advanced the exponential GARCH (EGARCH) model, which incorporates asymmetric effects in returns from speculative prices, where ω, α, β, and δ are constant parameters. The δ coefficient captures the asymmetric effect of previous shocks (Longmore & Robinson, 2004). The leverage effect can be tested if $\delta < 0$. If $\delta \neq 0$, the news impact is asymmetric. It means that positive shocks generate less volatility than negative shocks

In the TARCH model, good news, $u_{t-1} > 0$, and bad news, $u_{t-1} < 0$, have differential effects on conditional variance; good news has an impact of α while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, bad news increases volatility, and there is a leverage effect for the $i - th$ order. If $\gamma \neq 0$, the news impact is asymmetric.

When fitting GARCH models, one must specify the distribution of the standardized residuals—those residuals scaled by the model's time-varying volatility. The choice of distribution (Normal, Student's t, or Generalized

Error Distribution) reflects different assumptions about the shape of the error terms and, in particular, the prevalence of extreme values.

GARCH models require specifying the distribution of the standardized residuals (i.e., returns adjusted by the model's volatility). With a Normal (Gaussian) distribution, the residuals are assumed to be symmetric with relatively thin tails, potentially underestimating large shocks (Altman & Bland, 1995). Student's t retains symmetry but includes a degrees-of-freedom parameter for heavier tails, better capturing extreme events (Ahsanullah *et al.*, 2014). Generalized Error Distribution (GED) is also symmetric but offers a shape parameter that flexibly adjusts tail thickness, making it suitable for a wider range of kurtosis levels (Wiśniewska & Wyłomańska, 2017).

In all cases, these distributions are assumed to be independent and identically distributed (i.i.d.) for the standardized residuals, with zero mean and unit variance. The primary motivation for choosing one distribution over another is how well it captures the observed level of kurtosis (tail heaviness) and extreme events in the data.

The optimal model is chosen according to Akaike (AIC) and Hannan-Quinn Information Criteria.

Overall, these models are well-suited for modeling exchange rate volatility due to their flexibility, ability to capture volatility clustering, and capacity to account for asymmetric effects of market shocks. This leads to better risk assessment and more informed decision-making in financial markets.

III. Intraday volatility (OHLC)

Models that include open, close, high, and low prices are effective for modeling exchange rate volatility because they provide a comprehensive view of price movements within a given trading period. These prices capture essential information about market dynamics, and these models account for the full range of price activity within the period, reflecting intraday volatility and capturing extreme price movements that single-point estimates such as closing prices might miss.

High and low prices provide insights into the day's price extremes, showing the maximum potential volatility. Open and close prices indicate the direction and strength of market sentiment at the beginning and end of the trading period. These detailed price data models can produce more accurate and responsive measures of volatility, improving the prediction and management of exchange rate risks.

Let O_t, C_t, H_t, L_t denote the opening, closing, high and low prices at day t, respectively.

A simple measure of volatility is defined as the first logarithmic difference between the high and low prices (Alizadeh *et al.*, 1999; Gallant *et al.*, 1999):

$$V_{S,t} = \ln(H_t) - \ln(L_t) \tag{1}$$

The Parkinson (1980) volatility measure is an estimator of the true volatility of an asset's price, which assumes that the price follows a geometric Brownian motion with no drift. This measure is based on the range (high and low prices) of the asset over a certain period, typically a trading day. The formula for the Parkinson volatility estimator is given by:

$$V_{P,t} = 0.361R_t^2 = 0.361[\ln(H_t/L_t)]^2 \tag{2}$$

This estimator is often considered more efficient than the traditional close-to-close volatility estimators because it uses intraday high and low prices, which can provide more information about the true volatility of the asset.

Based on Chan and Lien (2003), $V_{P,t}$ may be up to 8.5 times more efficient than log-squared returns.

Another approach to estimating the true volatility of an asset's price is the Garman and Klass (1980) volatility estimator, which incorporates opening and closing prices in addition to high and low prices. The formula for the Garman and Klass volatility estimator is given by:

$$V_{GK,t} = \frac{1}{2}[\ln(H_t) - \ln(L_t)]^2 - [2\ln 2 - 1][\ln(C_t) - \ln(O_t)]^2 \tag{3}$$

The Garman and Klass estimator is designed to provide a more accurate measure of volatility by using the full range of daily prices, including open, high, low, and close prices. This method is considered to be more efficient and less biased than relying solely on closing prices, as it accounts for the intraday range and the difference between opening and closing prices.

According to Chan and Lien (2003), both measures are unbiased when the sample data are continuously observed with Vox, being more efficient than $V_{P,t}$.

When there is a non-zero drift term, both the Parkinson and Garman-Klass measures become inefficient (Chan and Lien, 2003). Hence, an alternative measure with independent drift is required.

Rogers and Satchell (1991) and Rogers, Satchell and Yoon (1994) propose a volatility measure which is subject to a downward bias problem:

$$V_{RS,t} = [\ln(H_t) - \ln(O_t)]\,[\ln(H_t) - \ln(C_t)] + [\ln(L_t) - \ln(O_t)]\,[\ln(L_t) - \ln(C_t)] \quad (4)$$

Heynen and Kat (1994) show that GARCH models outperform SV models in modelling exchange rates, while Kim *et al.* (1998) report that SV models are superior to GARCH models. Further, Hwang and Satchell (2000) argue that GARCH models are more suitable for describing volatility. Since there is no consensus, we will apply both types of measures (Floros, 2009).

Once volatilities are estimated, we run an Ordinary Least Square model to test if dummy series maturities and changes in the interest rate have a significant impact on exchange rate volatility:

$$xr = \alpha + \beta_{1(dummy\ derivatives)} + \beta_{2\ (dummy\ monetary\ announcements)} + \mu \quad (5)$$

where *xr*are exchange rate series (prices, yields and range volatility, conditional volatility) and β are the coefficients. Dummy derivatives is a series in which the observations from the last trading day to the maturity date of the exchange rate futures and options traded in MexDer take the value of 1, while the remaining observations are assigned a value of 0. Similarly, monetary announcements is a dummy series in which the dates of interest rate changes take the value of 1, while the remaining series are assigned a value of 0.

IV. Results

Table 1. *Descriptive statistics*

	OPEN	HIGH	LOW	CLOSE
Mean	17.9742	18.07547	17.88416	17.97523
Median	18.81342	18.91098	18.73004	18.814
Maximum	25.3151	25.76534	24.72803	25.3362
Minimum	11.9657	12.0474	11.9347	11.9805
Std. Dev.	2.841762	2.869722	2.814524	2.840592
Skewness	-0.590088	-0.571543	-0.608124	-0.590928
Kurtosis	2.530144	2.550318	2.504295	2.533825
Jarque-Bera	190.2007	177.857	203.3322	190.2623

Source: Own elaboration with estimation results.

As observed in Table 1, all skewness, Kurtosis, and Jarque-Bera series have negative skewness, implying that the distribution has a long-left tail. The empirical analysis reveals that all observed distributions exhibit kurtosis values below three, indicating that they are less peaked than a standard normal distribution. This suggests a tendency toward platykurtosis, a common feature in financial data characterized by lighter tails and a flatter peak relative to the normal distribution. Furthermore, the Jarque-Bera test results reject the null hypothesis of normality at the 5% significance level across all distributions. (Floros, 2009).

The results from the ADF unit root tests displayed in Table 2 indicate that all series are I(1), and therefore, quantitative models can be used to measure daily volatility. The ARCH-LM test was also performed to check whether the series has an ARCH effect or heteroscedasticity. As expected, the exchange rate returns show heteroscedasticity.

Table 2. *Unit root tests results*

	ADF					
	Intercept		Intercept and trend		None	
	Level	FD	Level	FD	Level	FD
Open	-1.956698	-51.89358***	-1.58835	-51.91206***	0.281931	-51.89613***
High	-2.036114	-23.03664***	-1.587183	-23.07671***	0.215402	-23.03347***
Low	-1.994716	-46.2508***	-1.623161	-46.27133***	0.284198	-46.25212***
Close	-1.992801	-52.06195***	-1.608267	-52.08016***	0.293674	-52.06463***

Source: Own elaboration with estimation results.

Table 3. *GARCH Models: Selection Criteria*

Distribution	NORMAL			T-STUDENT			GED		
Criteria	AIC	SCHWARZ	HQ	AIC	SCHWARZ	HQ	AIC	SCHWARZ	HQ
GARCH (1,1)	-7.20384	-7.19543	-7.20080	-7.25276	-7.24225	-7.24897	-7.24689	-7.23638	-7.24310
EGARCH (1,1)	-7.20722	-7.19670	-7.20342	-7.25954	-7.24693	-7.25499	-7.25067	-7.23806	-7.24612
TGARCH (1,1)	-7.20871	-7.19820	-7.20492	-7.25189	-7.23928	-7.24734	-7.25189	-7.23928	-7.24734

Source: Own elaboration.

As shown in Table 4, the coefficients of the applied EGARCH (1,1) t-Student model yielded statistically significant results at the 1% level. Furthermore, a leverage effect is confirmed since $\delta < 0$. It means that positive shocks generate less volatility than negative shocks. Furthermore, according to the EGARCH model applied, it has been concluded that there is no autocorrelation or ARCH effect, as both tests are at the 1% error level.

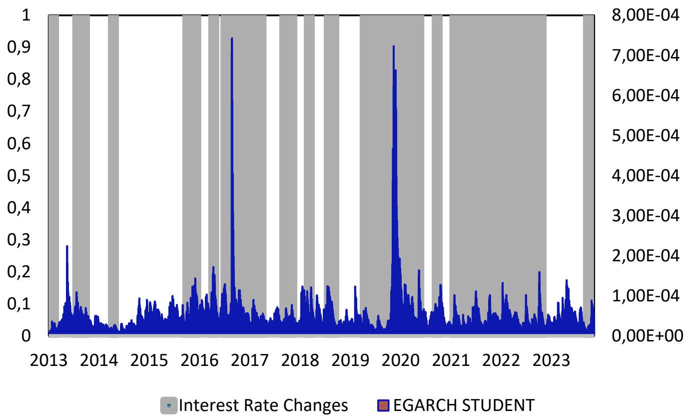
Figure 2 illustrates the conditional variance modeled using the EGARCH framework, highlighting its responsiveness to fluctuations in interest rates. The visualization clearly demonstrates how shifts in interest rates influence the behavior of conditional variance, capturing the dynamic relationship between monetary policy changes and market volatility.

Table 4. *EGARCH Results*

(ω)	-0.559144 (0.088044)
(α)	0.200771 (0.024799)
(β)	0.082897 (0.015129)
(δ)	0.959664 (0.007889)
ARCH (1)	0.243881 [0.6215]
Q^2 (5)	7.9057 [0.162]
JB	1416.624 [0.00]

Note: standard errors are reported in parentheses. P-values are reported in brackets. ***represents statistical significance at 1% levels.
Source: Own elaboration with estimation results.

Figure 2. *Conditional Variance: EGARCH (1,1) t-Student*



Source: Own elaboration with estimation results.

Table 5 shows the intraday volatility estimates, which complement the graphic analysis in Figure 3. We find strong evidence that daily prices can be characterized by volatility patterns and observe that prices exhibit all the financial stylized facts: clustering of volatilities, platykurtosis, and nonstationarity. Four models are used to calculate daily volatility. The results show that Vs, a simple volatility measure defined as the first logarithmic difference between high and low prices, overestimates Vgk, Vp and Vrs. In addition, it appears that the VRS measure has very similar dynamics compared to EGARCH volatility; however, VRS underestimates volatility, especially the extreme values observed in March 2020.

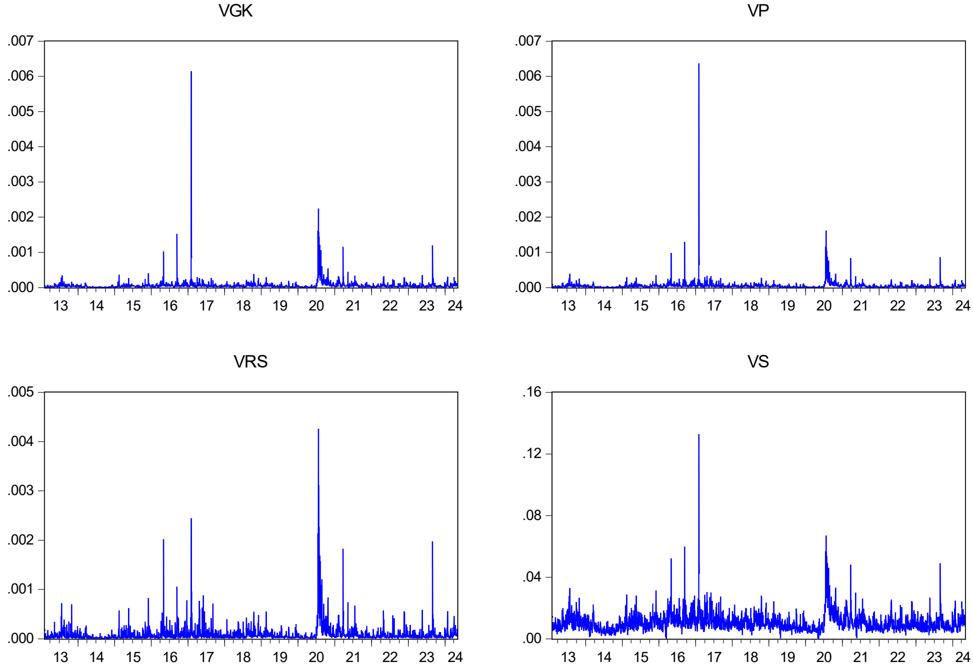
Table 5. *Volatility estimates*

	VGK	VP	VRS	VS
Mean	6.36E-05	5.31E-05	8.97E-05	0.010429
Median	3.69E-05	3.03E-05	4.54E-05	0.009164
Maximum	0.006148	0.006369	0.004259	0.132829
Minimum	0	0	0	0
Std. Dev.	0.000158	0.000146	0.000183	0.006191
Skewness	23.29981	30.47061	10.30006	4.922917
Kurtosis	808.2246	1261.39	165.3091	67.42533
Jarque-Bera	76684548	1.87E+08	3155351	500681.5
Probability	0	0	0	0
Observations	2829	2829	2829	2829

Source: Own elaboration with estimation results.

As observed in Table 6, the maturity of derivative contracts appears to have a negative effect on the exchange rate and intraday volatility. Interest rate changes have a negative impact on exchange rate returns and intraday volatilities, but a positive impact on the exchange rate and conditional volatility. It seems that the maturity of derivatives only has a significant impact on the exchange rate, while monetary policy announcements have a significant impact on both the exchange rate and conditional volatility.

Figure 3. *Range/Intraday Volatility*



Source: Own elaboration with estimation results.

Table 6. *OLS results*

Series	Maturities Coef.	IR Changes Coef.
XR prices	-0.450405***	1.426047***
XR_Returns	0.000604	-0.001213
VGK	-6.55E-06	-3.15E-06
VP	-6.33E-06	-5.43E-06
VRS	-9.19E-06	1.91E-06
VS	-0.000455	-0.000165
EGARCH	7.00E-07	2.63E-05***

Source: Own elaboration with estimation results.

Conclusion

We estimate exchange rate volatility employing four measures of intraday volatility and three GARCH models assuming three probability distributions (Gauss, t-Student and GED).

The findings suggest that intraday volatility, measured by considering the opening, closing, peak and trough data, behaves differently from conditional volatility as measured by GARCH models.

Based on the results, it appears that intraday volatility underestimates the exchange rate risk. The regression results suggest that the maturity of futures and options in the derivatives market tends to have a negative impact on exchange rate volatility. However, this effect is not statistically significant, except for the MXN/USD spot price. Likewise, it seems that monetary policy announcements provide certainty to the market and have a statistically significant effect on spot prices and conditional volatility.

The empirical findings reveal critical insights into how derivative contract maturity and interest rate changes influence exchange rates and market volatility, carrying significant implications for both policymakers and market participants. For policymakers, the notable impact of monetary policy announcements on exchange rates and conditional volatility underscores the importance of clear and consistent communication strategies.

Central banks must carefully manage how they convey policy decisions to prevent excessive market volatility and uncertainty. Additionally, since interest rate adjustments negatively affect exchange rate returns and intraday volatility while positively influencing exchange rates and conditional volatility, policymakers need to balance their objectives of economic stabilization with the potential risk of increased market instability.

Regulatory oversight of derivative markets may also need to be strengthened, particularly to encourage longer-term contracts that could contribute to exchange rate stability and monitor speculative trading activities that might amplify volatility.

For market participants, these dynamics suggest the need for more strategic risk management and investment approaches. The influence of derivative contract maturity on exchange rates implies that traders and investors should carefully choose the maturity structure of their hedging instruments to mitigate exposure to short-term volatility. Moreover, the complex effects of interest rate changes highlight the importance of incorporating interest rate sensitivity into currency strategies.

Investors must adapt by employing dynamic hedging techniques and potentially leveraging volatility-based trading strategies during periods of monetary policy shifts. Staying attuned to central bank signals becomes increasingly important for anticipating market movements and making informed decisions. In this environment, portfolio diversification and sophisticated risk management become essential tools for managing exposure to the dual risks of fluctuating returns and heightened volatility driven by both derivative market dynamics and monetary policy actions.

The future research agenda could include other approaches, such as NARDL or multivariate GARCH models, as well as the analysis of the interrelationships between the intraday volatility of the stock market, oil prices and exchange rates.

Ethics Statement

This research article did not work with a person or group of persons to generate the data used in the methodology; therefore, it did not require the endorsement of an Ethics Committee for its execution.

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