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Functional study of stock market volatility and option contracts; Investments in the Mexican derivatives market (MexDer)

Estudio funcional de la volatilidad en bolsa y los contratos de opciones; las inversiones en el mercado mexicano de derivados (MexDer)

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Abstract

Speculative investments in option contracts show an erratic movement in this period. Agents seek to hedge against risks and obtain safer returns, given the growing volatility of the markets. The ARCH and GARCH methods were applied, tools to perceive the degree of volatility in option investments. Through the estimation of parameters, the volatility of the market was able to verify its persistence with the stock market index; that induces investors to change strategies. An instability that makes the GARCH process valid, since the presence of heteroskedasticity allows certain adjustments. Indeed, the volatility and variance do not become constant, as the implicit factors change, they tend to affect the behavior in the period. All this allows inferring the best investment policies in the case of options.

JEL Code: G12, C51, C22, C16
Keywords: ARCH; GARCH; backtesting; underlying assets; risks and degrees of volatility

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Resumen

Las inversiones especulativas en contratos de opciones muestran un movimiento errático en este periodo. Los agentes buscan cubrirse frente a los riesgos y obtener rendimientos más seguros, ante la creciente volatilidad de los mercados. Se aplicó los métodos ARCH y GARCH, herramientas para percibir el grado de volatilidad en las inversiones de opciones. Por la estimación de parámetros, la volatilidad del mercado se logró verificar su persistencia con el índice bursátil; que induce a los inversionistas a cambiar de estrategias. Una inestabilidad que hace que el proceso GARCH sea válido, toda vez que la presencia de heterocedasticidad permite ciertos ajustes. En efecto, la volatilidad y la varianza no llegan a ser constantes, a medida que cambian los factores implícitos suelen afectar el comportamiento en el período. Todo ello, permite inferir las mejores políticas de inversiones en el caso de opciones.

Código JEL: G12, C51, C22, C16
Palabras clave: ARCH; GARCH; backtesting; activos subyacentes; riesgos y grados de volatilidad

Introduction

Option contracts remain a good investment alternative (Sosa & Ortiz, 2017), which depends on the degree of volatility of their implicit assets.[1] They reflect strong variability and fluctuations in the stock market index (Uribe & Fernandez, 2014; Moretti, 2015) and other variables such as interest and exchange rate. An increasingly important flow of capital is shifting toward this derivative.[2] Nevertheless, volatility is a recurring theme in the prices and risks of derivative products.

Any investment with an underlying asset's implicit guarantee, such as shares and potential returns, makes it more attractive. A good part of financial investment is concentrated in this instrument (Hull, 2017; Miller, 1992), a corporate treasury strategy that avoids riskier financial positions. Studies have been carried out on seeing contagions and bubbles in the stock market from oil movements (Zhao, Wen, & Li, 2021) and identifying market patterns (Soni *et al.*, 2022). It is feasible to observe the persistence of volatility in other assets, such as gold and oil (Yaya *et al.*, 2016).

This work analyzes the behavior of the monthly Stock Market Index (PQI, Prices and Quotations Index) series volatility and its connection with the monthly amounts of the options contracts from 2010 to 2018. Observing investment strategies is about analyzing volatility to see its behavior and risks and anticipate investment policy. This is sufficient to identify if it follows a pattern or trend over the period. The central hypothesis states that the PQI volatility influences the investment decisions of options as a hedging instrument. Given the risks, it is possible to verify how the intrinsic factors behave within that

[1]Operations with risk hedging instruments, which have an underlying asset (commodities, stock indices, etcetera) and are subject to variations in their market prices. In Mexico, there are more and more operations in futures and options exchanges.
[2]In Mexico and Brazil, derivatives markets are the most important and move large amounts of capital (Moretti, 2015).

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volatility based on applying the ARCH and GARCH methods and to obtain some statistical indicators confirming their value and significance.

This paper is organized into sections. First, a brief theoretical framework and review of the literature on volatility in stock markets are presented to avoid confusing it with risk as a factor. Then, the zigzagging behavior of option contracts, first with the stock index and then with stocks, is examined over this period.

All this is based on the proposal of a methodology that enables posing and describing the problem. Volatility is the central theme, which identifies how stochastic processes occur. ARCH and GARCH are used for monthly option amounts from January 2010 to December 2018. Next, a review of the empirical evidence is made, and then inferences are made from the results regarding the volatility of the option amounts versus the different market actions.

Theoretical framework

Financial liberalization and the entry of foreign capital made the currency stronger (Basilio, 2018), which brought about unusual development in the Mexican Derivatives Market (MexDer). Now there is a high degree of integration of the Mexican market in global markets. This fact is confirmed by López-Herrera *et al.* (2015), who show volatility transmitted by international markets to the country due to the flow of capital and the participation of foreign investments. In this sense, option contracts for treasuries became an instrument that hedges risks and offers a higher return.

Considering this market risk situation leads to studies on volatility[3] in returns for asset prices and options. Volatility refers to the intensity of changes in a variable, measured by the standard deviation (σ) or variance ($\sigma 2$)[4]. An estimate of volatility[5] in asset prices or the underlying return of an option is a warning of its risks.

There is a stochastic part in the options markets, and it is not easy to distinguish a trend by its high volatility. This market instability is due to a high-risk exposure, implying that option contracts lead to long-term returns and are not characterized by a normal distribution.[6] This situation merits the

[3]Volatility is reflected by the conditional variance of asset returns, these factors being important in option pricing and the financial market (Tsay, 2002; Aguirre *et al.*, 2013).
[4]Poon and Granger's (2003) equation measures the dispersion of a random variable by: $\sigma^2 = \frac{1}{N-1}\sum_{t=1}^{N} (R_t - \bar{R})$. Where σ^2: variance, N: No. of observations, $\bar{R}$: Mean of the returns, R_t: Returns.
[5]The Value at Risk (VaR) method is used in the measurement of volatility, under the assumption of a normal distribution in asset value variations.
[6]Without prior knowledge of their distribution function being a requirement (Bariviera *et al.*, 2017; Katsiampa, 2017; González, Mora, & Solano, 2015).

application of the GARCH (Generalized Autoregressive Conditional Heteroscedastic) method. The volatility is not only perceived with this model, but it enables the advantage of making an "optimal weighting" of the historical information based on its generalization[7] and conditional volatility (Ruiz & Mosquera, 2021), especially when there is the characteristic that the observations of financial variables have a high frequency. In Sheppard's model (2020), it is established that the fluctuations and variations observed in the statistical series can evidence the trends and improve the volatility parameter estimates with the conditional variance data and the number of lags in the disturbances.

Kaminski's (2013) work used the GARCH process in the options market in the case of the Warsaw Stock Exchange. The author managed to observe the heteroscedasticity in stock returns caused by volatility in their prices. In Chorro *et al.* (2012), the need for new dynamic pricing models of the underlying asset for options is affirmed, and the ability to produce minimal errors in pricing is evaluated.[8] Arenas and Fernandez (2020) specify the equation for identifying volatility using the GARCH method, incorporating lagged conditional variance and lagged or prior period shocks.

Some research[9] shows that verifying the existence of heteroscedasticity in stock returns avoids the bias between real and observed prices. When measuring the volatility of a financial time series, of course, it cannot be assumed to be constant and of homoscedastic variance (Casas & Cepeda, 2008); rather, this serves to make models with past information and to specify forecasts and projections on short and long positions in the holding of an asset, for possible risk management (Solís & Muñoz, 2022). This fact undoubtedly enables relevant parameters to be obtained since there is a substantial reduction in the volatility of stock portfolio prices. When analyzing this procedure in Mexico, it is necessary to consider factors that affect underlying asset volatility.[10] Of course, they impact the trading of option contracts (Hernández-Trillo, 1997).

Methodology proposal

Problem statement

Often, volatility cannot be determined or identified directly in the financial asset, so proxy volatility measures are used (Danielson, 2011). This paper considers volatility using the ARCH and GARCH

[7]Historic series of implicit assets may be described by GARCH-type models, which lead to results in asset returns with a generalized conditional distribution.
[8]Stochastic Black-Sholes, Heston and GARCH group stochastic models have been used (Kaminski, 2013).
[9]The work of Duan (1995) and Heston and Nandi (2000) used the GARCH process and achieved good results in the face of deviations in option prices.
[10]It is difficult to monitor changes in the variances and behavior of derivatives, according to Hernandez-Trillo (1997), who used the GARCH method to monitor the volatility of stock returns.

models, which leads to defining the financial series' stationarity (Ruiz & Mosquera, 2021). In options markets, the valuation of contracts requires knowledge of the behavior of some variables, such as the prices of the underlying asset, the exercise price, the option price, the volatility of the asset, the risk-free interest rate, and the maturity (Benavides, 2006; Hull, 2009; Blair, Poon, & Taylor, 2001). A mispricing model causes errors in trends and becomes an invalid measure of volatilities (Harvey & Whaley, 1992; Benavides, 2006).

In some markets, high price volatility was found.[11] The prices of securities are fixed by the nominal value, which is determined at the time of issuance, but the value moves according to future payments (Campbell & Cochrane, 2000; Cochrane, 1999) at a discount of a random rate over time. Of course, this will depend on the company's financial performance, and the variability of its returns is part of this volatility.

In order to formulate the problem, it is first recognized that the stock market's volatility—through the PQI—becomes an explanatory variable. The nature of the volatility[12] in the stock market index is transmitted to the contract amounts of the options. The conditional variance of each shock u_i in the explanatory variables is not necessarily constant but moves dispersedly, giving it the category of volatile (Maddala, 1994). This alters the stability of the financial market and investment decisions.

Option contracts operations, rather than a liquidity mechanism at a future term, arose from the probability of a higher return. It increases the risk and volatility in the markets. The contemplation of using an underlying asset, whose exercise price[13] involves the right to exercise or not, becomes a reason for high speculation compared to other instruments. Since Black and Sholes (1973), a way of evaluating the price of options[14] has been devised in the face of this instability. It is sometimes incomprehensible and not representative due to the high volatility of the markets, which is high and intensifies in the case of options.

Methodological development and statistical series

A monthly statistical series of option contract amounts was used for a more in-depth volatility analysis from January 2010 to December 2018. There are 108 observations, whose data source was the Mercado

[11]In studies of the US stock market, its high volatility is attributed, in turn, to the strong economic and commercial activity and the exploitation of financial markets (Schwert, 1989).
[12]With a not very volatile reference asset, there is no incentive to contract options. However, speculation increases when this volatility increases, because the options and the volatility are linked (Rodríguez, 1995).
[13]Price fixed in the contract to give the holder the right, not the obligation, to buy (call option) or sell (put option) the underlying asset at a given date (Rodriguez, 1995).
[14]It estimates the present value of an option to buy (Call), or sell (Put) those underlying assets or shares at a future date.

Mexicano de Derivados S.A. (MexDer). The underlying assets were taken as the Price and Quotations Index of the Stock Exchange.

Using a time series from 2010-2018 made it possible to move away from irregular behaviors and identify stochastic processes. Not so the 2008-2009 and now 2017 crises, which represented a difficult external context and much instability in international markets; when Donald Trump assumed the presidency of the United States (2017), uncertainty worsened and was felt by the markets with greater volatility.

In any time series Z_1, Z_2, ... Z_n, of underlying assets, such as stock indices, it is not easy to distinguish the existence of stochastic processes. Z_t is a random variable at a time t. When the N observations change from one level to another without a visible pattern, it is possible to state that there is a stochastic or random trend, which manages to define a sequence of values at different times. The random walk becomes[15]:

$$Z_t = \mu + \gamma Z_{t-1} + A_t \quad \text{For all } t = 0, +1, +2... \tag{1}$$

The coefficient γ has a condition of strict stationarity, provided that $\gamma < 1$ is satisfied (Gourieroux, 1997; Engle & Bollerslev, 1986). The parameter μ can be zero. A_t, a random variable, is described as white noise and variance Var $(U_t) = \sigma^2$ (Engle, 1982). A_t has zero mean and constant variance: $A_t \rightarrow (0, \sigma^2)$. Each A_t can follow a normal, normal white noise, or Gaussian distribution[16].

Volatility is usually described as a conditional variance[17] of a random variable (indices or returns of an asset) and a risk factor. This fact requires heteroscedasticity to be measured (Engle, 1982), a condition and procedure for assessing the quality of the parameters.

In a stochastic (univariate) process, the Z_t component follows an ARCH model. The conditional variance of the Z_t errors follows a function of Z_{t-1}, with no autocorrelation, which is statistically independent. The ARCH process involves a problem at the time of its application. As the number of lags

[15]A first order auto-regressive equation: $Z_t - \gamma Z_{t-1} = A_t$. Where Z_t is the variable or the return of the financial asset at time t, A_t represents the matrix of residuals or disturbance errors.

[16] Abascal (2016) points out that Granger and Andersen (1978) incorporate a conditioning variable of the previous period (t-1), in addition to the white noise term(A_t).

[17]The conditional variance of each disturbance ui in the explanatory variables is not necessarily constant but moves in a dispersed way and gives it the category of volatile (Maddala, 1994). In Griliches and Intriligator (1986) it is observed that there is heteroscedasticity (not equal variance), which is represented by: E (u2) = σ2. The conditional variances of ui are no longer equal or constant over the period.

grows, there are many iterations in the estimation process (Abascal, 2016). In Bhattacharyya and Ritolia (2008), it is described as follows:

$$Z_t = \sigma A_t \text{ with } \quad \sigma^2 = a_o + a_1 Z^2_{t-1} \tag{2}$$

The variable Z_t depends on σ, the volatility at time t, and A_t is the stochastic part of the model, which depends on the residuals. Where a_o, $a_1 > 0$, with $a_1 < 1$. $A_t \rightarrow (0,1)$, it is independent of σ.

The GARCH model is then considered to incorporate conditional volatility, making the estimates more efficient[18] than the ARCH model's. A stochastic process around Z_t can follow a GARCH process, thus:

$$Z_t = \sigma A_t \text{ with } \quad \sigma^2 = a_o + a_1 Z^2_{t-1} + b_1 \sigma^2_{t-1} \tag{3}$$

The conditional variance of the errors Z_t becomes a constant. The components of Z_t are not autocorrelated, being statistically independent and the conditional variance of Z_t being as a function of Z_{t-1}. Where a_o, $a_1 > 0$, with $b_1 > 0$, then $(a_1 + b_1) < 1$. If $A_t \rightarrow (0,1)$, it is independent of σ. In a large period, σ is the volatility coefficient at time t, which depends on the residuals ε_t, enabling the design of an ARMA (Auto-regressive moving mean)[19] structure. Thus, the conditional volatility depends on the squared residuals ε^2_{t-1} (ARCH effect) and the prior conditional variance σ^2_{t-1}.

Currently, the research includes an ARCH model that is improved by incorporating a lagged conditional variance (Nelson, 1990; Mora et al., 2014). These recent values bring with them some inertia from the past. This process estimates the degree of conditional volatility of returns (z_t) from a lagged variance or past volatility and then assumes a higher relative weight on current volatility (Bollerslev, 1987).

Therefore, the option's valuation is subject to the swings or volatility of the market and the movements recorded by its underlying asset (Hull, 2017). The most appropriate tools for detecting the degree of volatility are the ARCH and GARCH models since they capture behavior and volatility. It is usually reflected in the risks in which the potential financial returns reside.

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[18] According to Bollerslev (1987) and Nelson and Cao (1992), the parameters of the GARCH method have to meet the constraints $\alpha o > 0$, $a1 \geq 0$ and $b1 \geq 0$; of non-negativity; a positive conditional volatility; and that the process is proceeding. In the case that the parameters are $(a1 + b1) \leq 1$, there is a GARCH (1,1) model characterized by a stationary variance and convergence to a constant value (Faure & Scheidereiter, 2017; Gourieroux,1997) and ergodic as the sample grows (Hamilton, 1994).

[19] For more information, see Arango and Arroyave (2016)

Empirical evidence

There is no single process for identifying a series' volatility, but ARCH and GARCH are used here. These enable the observation of the trend of the returns of financial assets, such as the Price and Quotations Index (PQI). Recent works deal with the volatility and contagion of stock and stock market returns (Ramírez-Silva et al., 2018). Reyes-Garcia et al. (2018) did so for the PQI, comparing different volatility models with regime shifts and stochastic jumps occurring due to structural changes. The higher volatility of asset prices, such as stocks, implies higher market risk. Good gains can be achieved, but also heavy losses. It is often linked to the behavior of the stock index and other assets, such as the international price of oil and gold, which negatively affect the PQI in the long term (Singhal et al., 2019).

The increasing flow of investments into options contracts is due to the strong correlation with stock market indexes (PQI), particularly with a group of stocks that function as underlying assets. As confidence grows, despite the increasing risk, investments in options become attractive because they are subject to bond securities, which are backed by the good financial performance of the companies.

In the period 2010 to 2018, an efficient management of capital, it seems, favored a greater number of operations in options. However, during this period, the total number of contracts increased from \$3 967.1 in 2010 to \$1 627.9 million in 2018, a drop of 59% and a very unstable evolution over time (Table 1). Option investments were mostly distributed as underlying assets in stock index contracts (CPI). In 2010 transactions in these indexes amounted to almost 96% of the total, while in 2018 they accounted for almost 16.3% of the total.

Table 1
Amount of Options Contracts by Two Types of Underlying Assets, 2010-2018 (Millions of dollars per year)

Year	Stock Indices (PQI)	% of total	Stocks	% of total	Total amount
2010	3807.3	95.9	154.2	3.9	3971.5
2011	1899.2	94.9	99.1	4.9	2001.8
2012	1.3	0.7	171.6	91 .1	188.5
2013	1767.7	86.7	87.0	4.3	2039.8
2014	1.7	0.4	131.7	31.3	421.1
2015	2530.1	76 0	37.2	1.1	3331.2
2016	1345.8	78.7	35.4	2.1	1709.3
2017	558.7	37.3	39.4	2.6	1498.5
2018	259.5	16.3	96.6	6.1	1592.0

Source: created based on data from Mercado Mexicano de Derivados, S. A. (MexDer).

Regarding equities, options transactions moved more toward certain groups of assets[20]: América Móvil, Cemex, Walmex V, Grupo México, Femsa, Naftrac 02, and WalMart. Resources or funds in this type of option contracts and transactions were achieved of USD 154.2 million in 2010, while they were USD 96.6 million in 2018 (Table 2). There was no stability in the amounts of the options, due to the preference for some issuing companies, and there was an intense variability of the shares throughout the period.

Table 2
Amount of Stock Option Contracts, 2010-2018 (Millions of dollars per year)

Concept	2010	% of Total	2011	% of Total	2012	% of Total	2013	% of Total	2014	% of Total	2015	% of Total	2016	% of Total	2017	% of Total	2018	% of total
Stocks	154.2	3.9	99.0	4.9	171.6	91.1	87.0	4.3	131.7	31.3	37.2	1.1	35.4	2.1	39.4	2.6	96.6	6.1
American movil L	44.0	1.1	32.7	1.6	6.0	3.2	47.4	2.3	4.6	1.1	0.8	0.0	7.7	0.5	13.8	0.9	6.9	0.4
Cemex	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.5	0.2	1.4	0.1	1.4	0.1
Cemex CPO	12.3	0.3	0.7	0.0	12.0	6.4	1.0	0.1	21.5	5.1	0.0	0.0	0.0	0.0				
Walmex V	70.2	1.8	16.2	0.8	31.4	16.6	22.9	1.1	72.7	17.3	0.0	0.0	0.0	0.0				
Televisa CPO	10.1	0.3	3.4	0.2	0.6	0.3	0.0	0.0	1.5	0.4	0.0	0.0	0.0	0.0				
Gmexico	15.0	0.4	46.0	2.3	0.6	0.3	14.0	0.7	11.8	2.8	10.5	0.3	13.4	0.8	2.0	0.1	4.1	0.3
Femsa									7.2	1.7	0.8	0.0	1.7	0.1	0.5	0.0	28.8	1.8
Mexichem									0.0	0.0	0.0	0.0	1.0	0.1	3.7	0.2	0.0	0.0
Telmex L	2.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0		
Mextrac	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0		
Naftrac 02	0.3	0.0	0.0	0.0	121.1	64.2	1.7	0.1	12.3	2.9	3.7	0.1	0.0	0.0	0.1	0.0	0.0	0.0
Bitrac	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0		
Televisa											0.0	0.0	1.2	0.1	4.7	0.3	0.0	0.0
Walmart											21.3	0.6	7.0	0.4	12.1	0.8	53.0	3.3
Afa															1.0	0.1	2.3	0.1
Lala															0.0		0.0	0.0

Source: created with data from Mercado Mexicano de Derivados, S. A. (MexDer).

Application of the ARCH and GARCH method; their results

The volatility analysis was carried out using the ARCH and GARCH methods, with 108 observations of the monthly amounts of option contracts from 2010 to 2018. The choice of this period complies with the regularity of this instrument's operations following the 2008-2009 crisis. In particular, the stochastic processes and the conditional volatility of the stock market index (PQI) were examined, based mainly on the GARCH process.

[20]The Mexican stock market is characterized by a small number of issuers, with large capitals and high concentration of partners. Some capitals become illiquid, compared to other stock markets (Guillén, 2012).

There are differences in the ARCH and GARCH models that are applied in regime-switching schemes, which are persistent in volatility and take different values with high and low levels of volatility. The GARCH process comes to be characterized by an exponential drop in the auto-correlation of its conditional variance. It occurs for absolute returns and when financial assets have had a serial, slow, and decreasing correlation in long series (Poon & Granger, 2003).

Regarding option contract amounts, between 2010 and 2018 there was an average μ of $190.98 million per month (Table 3). The amounts went from a low of $25.07 million to a high of $851.11 million per month. The median was $155.04 million. The kurtosis coefficient was 7.65, greater than 3, representing a leptokurtic distribution with high kurtosis toward one side. The skewness was 2.43. There are the conditions of a stochastic and conditional Gaussian process by registering a rather high kurtosis (C).

Table 3
Basic Indicators, 2010-2018

Descriptive Statistics	
Mean	191.0
Standard deviation	145.0
Standard error	14.1
Skewed	2.4
Kurtosis	7.6
Mode	n.a.
Median	155.0
Rank	826.0
Minimum	25.1
Maximum	851.1
Q1	105.3
Q2	155.0
Q3	220.3

Source: created with data from MexDer.
n.a. Not available.

In this period analyzed, from the parameter estimates with GARCH (1,1) in the different cases, Normal Distribution, T-Student, and Generalized Error Function (GED), it was possible to verify that at least three rules are fulfilled (Table 4):

a) The parameters α_o, α_1 and β_1 are positive values: α_o = 41 637.78; α_1= 0.14 and β_1=0.14.
b) The sum of α_1 and β_1 is less than unity: $(\alpha_1 + \beta_1) <1$. There is persistence in the speed and reversion of the errors concerning the mean. As the sample size increases, the GARCH

process results are strictly stationary and ergodic[21] under convergence conditions closer to the mean μ.

c) The parameter β_1 is non-zero, weakly positive, reflecting that the monthly amount series contains a skewness toward one of the sides but without possessing thick tails.

Table 4
Application of GARCH to Options Contracts: Estimated Parameters (Millions of Dollars)

Parameters	Garch-values (1,1) [Normal Distribution]	Garch-values (1,1) [T-Student]	Garch-values (1,1) [Generalized Error Function (GED)]
μ	190.98	190.98	190.98
α_0	41 637.78	41 637.78	41 637.78
α_1	0.14	0.14	0.14
β_1	0.14	0.14	0.14
V	-	5.00	2.00

Source: created based on MexDer data.

The estimation of the parameters α_0, α_1, and β_1 comply with the non-negativity of their values, in addition to the fact that the sum of α_1 and β_1 is less than unity. This implies that the results obtained with the GARCH process are valid, since the quasi-maximum likelihood method was used, as it is an iterative process and more efficient. The standard errors obtained indicate that they are robust, and it is also inferred that the conditional variance has an almost homoscedastic distribution throughout the period.

In assessing the relevance of the null hypothesis, the various white noise and normal distribution tests, given the P-value, yield neither valid nor significant results at a 95% margin. In this case, the returns do not necessarily explain the contract amounts (Table 5). To verify that conditional heteroscedasticity exists, the Arch effect (which includes lagged periods t-1) and a P-value of 8.38 (which is a high value) give a somewhat satisfactory result. Therefore, it is inferred that the lags in the residuals do not determine the process of conditional volatility in option prices at the current time.

[21]There is an independent distributed sequence with mean μ that converges toward a point as the samples grow (Grimmett & Stirzaker, 1992).

Table 5
Significance Tests

Tests	p-value	Meaning	
White-Noise	0.000	False	
Normal Distribution?	0.000	False	
ARCH Effect?	8.380	False	
Residuals Objective	**P-value**	**Meaning**	**Significance Test at 5.00%**
0.000	0.00%	True	
0.000	0.00%	True	
0.000	0.00%	True	

Source: created based on Mexder data.

In the normality tests of the data, the values of the Jarque-Bera (JB), Shapiro-Wilk (SW), and Doornik-Hansen (Chi-Square) statistics show results that are ultimately false or not taken as valid, at a significance level of 95% (Table 6). In all three cases, the P-values are not greater than 0.050, so the assumption of normal distribution for the sample data set is incorrect. The Shapiro-Wilk statistic was very low, the fit was poor, and normality was rejected. For a bivariate test of variables, the Doornik-Hansen (Chi-Square) value of 136.11 also rejects the normality of the data, so the estimated parameters are not as reliable.

Table 6
Normality tests at 5.00%

Tests	Score	CV	p-value	Meaning
Jarque-Bera	332.17	5.99	0.000	False
Shapiro-Wilk	0.76	n.a.	0.000	False
Doornik-Hansen (Chi-Square)	136.11	5.99	0.000	False

Source: created with data from MexDer.
n.a. Not available.

Option contracts strictly taking the stock market index (PQI)as an underlying asset

Within the options contracts, the underlying asset used most frequently is the Mexican Stock Exchange's Price and Quotations Index (PQI). This index reflects the performance of shares on the Mexican Stock Exchange, which in turn represents the progress of economic activity. There is a relation of production and investment variables with financial market returns (Alonso-Rivera et al., 2017). Investments in productive sectors and the growth of industrial production, as part of the real sector, positively impact stock prices and the PQI.[22]

The conditional volatility of options is stochastic and unstable when taking the stock market index. Aguirre et al. (2013) found frequent correlations between options and stock indexes for these financial series. Residuals were used to achieve good estimates of the stock returns reported by the PQI as an underlying asset in the options. Using the GARCH (1,1) model was a resource and test of volatility, making the estimates more efficient than those obtained with the ARCH.

According to data from the Mexican Stock Exchange, the PQI reported a mean μ of 42 206.06 points, with a standard deviation of 5 151.24 from 2010 to 2018 (Table 7). A low volatility of the stock market index was observed, with a coefficient of variation of 12.2% to the mean. Accordingly, there was a lower risk per unit of return. There was a skewness of -0.4 and a kurtosis coefficient of -0.6, with both being negative and less than unity. This represented a less pointed distribution (platykurtic) with thicker tails.

Table 7
Basic Standards, 2010-2018

Descriptive Statistics	
Mean:	42 206.06
Standard deviation:	5 151.24
Standard error	n.a.
Variation Coefficient	12.2
Skewness:	-0.4
Kurtosis:	-0.6
Median:	43 061.58
Rank:	20 818.87
Minimum	30 391.61
Maximum	51 210.48
Q1	38 608.81
Q2	45 749.3

Source: created with data from the Mexican Stock Exchange.
n.a. = Not available.

The movements of the Price Index oscillated widely, from 20 818.87 points to a maximum of 51 210.48 points in this period.

[22]For Bond, Edmans, and Goldstein (2011), the availability of less information and the degree to which the individual takes advantage of it to make decisions is crucial, if market prices are to be an absolute guide to investments, and in this case PQI variations are taken.

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Table 8
GARCH Price and Quotations Index (PQI) GARCH Method: Estimated Parameters (Points)

Parameters	Garch-values (1,1) [Normal Distribution]	Garch-values (1,1) [T-Student]	Garch-values (1,1) [Generalized Error Function (GED)]
μ	42 206.06	42 206.06	42 206.06
α_0	125 996 575.95	125 996 575.95	125 996 575.95
α_1	0.5	0.5	0.5
β_1	0.5	0.5	0.5
v	-	0.5	

Tests	p-value	Meaning	
White-Noise	0.00%	False	
Normal Distribution?	11.97%	True	
ARCH Effect?	0.00%	True	

Residuals Objectives	P-value	Meaning	Significance Test at 5.00%
0.00	0.00%	True	
0.00	5.40%	False	
0.00	8.77%	False	

Source: created based on data from the Mexican Stock Exchange.

The GARCH model has always been effective and is useful in detecting conditional variance and the degree of volatility (Engle, 2001). From the parameter estimates with GARCH (1,1), for the cases of normal distribution, t-Student, and the generalized error function, it was possible to verify that the three rules are satisfied:

a) The parameters α_{or}, α_1 and β_1 are positive values: α_{or}=125 996 575.95; α_1= 0.47 and β_1=0.47.
b) The sum of α1 and β1 is 0.94, less than unity: (α1 + β1) <1. There is persistence in the speed and reversion of the errors concerning the mean. The GARCH process is strictly stationary, under conditions of convergence to closer to the mean μ, as the sample size increases.

The parameter β_1 of 0.47 is non-zero. This parameter reflects that the PQI is skewed toward one of the sides, as seen in Figure 1.

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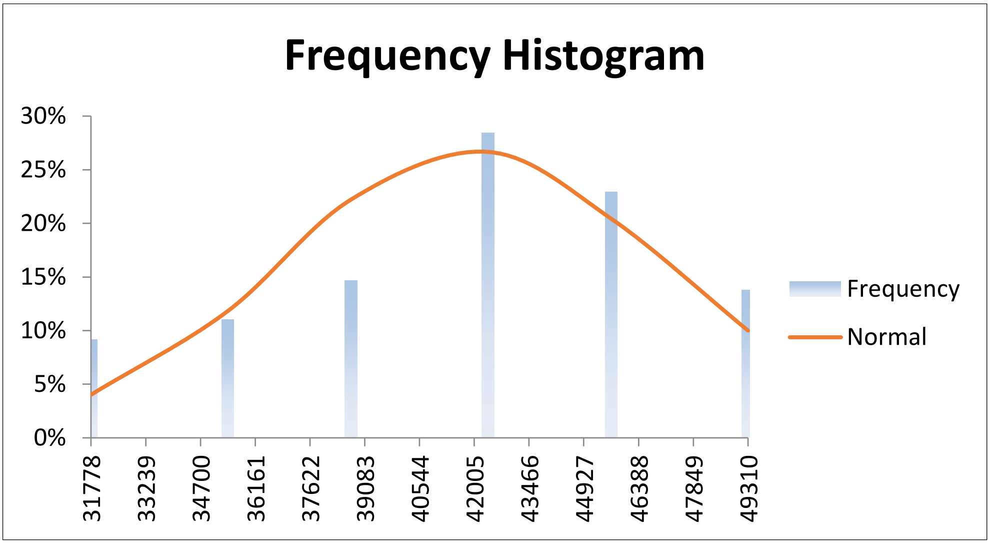

Figure 1. Distribution of data over the period 2010-2018
Source: created with data from the Mexican Stock Exchange.

By obtaining values of the estimated parameters α and β_1, although they comply with the non-negativity of their values, it is also observed that the sum of α_1 and β_1 was less than unity. This fact makes the results obtained by the GARCH process valid, based on the quasi-maximum likelihood method. The standard errors are robust, and the conditional variance is inferred to have a homoscedastic distribution throughout the period analyzed.

When the normality tests were conducted, the Jarque-Bera (JB) and Shapiro-Wilk (SW) statistics yielded true and meaningful results at the 95% level (Table 9). In these two cases, the residuals and the P-value are greater than 0.050, which is quite high. The normality of the data distribution is valid. Although the Jarque-Bera and Shapiro-Wilk statistics are low, the fits and normality are good. On the other hand, the Doornik-Hansen test (Chi-Square) of 7.34 does not accept the normality of these data; consequently, the values obtained are not significant.

Table 9
Normality Tests of the Price and Quotations Index (PQI)

Types of Tests	Score	CV	p-value	Meaning of the result
Jarque-Bera	4.25	5.99	12.0%	True
Shapiro-Wilk	0.98	n.a.	8.4%	True
Doornik-Hansen (Chi-Square)	7.34	5.99	2.6%	False

Source: created based on data from the Mexican Stock Exchange.

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Analysis and inferences from these results

Possibilities in market predictions, the use of backtesting

The use of algorithms in financial markets due to advances in computer science has gained popularity in recent years (Kostiainen, 2016). The convenience of applying backtesting is not only about testing what would have happened with a certain strategy in cases where time series are used but also comparing one strategy against another[23] by distinguishing the margins for and against (Lopez, 2022). Predicting results leads to finding the best strategies in such situations and risk conditions in the market.

Regarding price prediction in financial markets, Ke Li (2022) states that many analysis techniques have been used to identify patterns. Nonetheless, new techniques are always being explored through the automatic execution of algorithms, such as the machine learning model, to see predictions in the movement of stocks in the markets (Estupiñan, 2022).

Particularly, the backtesting technique enables the validation of results in time series, in which the hyperparameters can be found. A procedure for separating data into periods is conducted; in this way, iteration processes are conducted (Estupiñan, 2022), resulting in locating the best fit of the data. Nevertheless, limitations are perceived in finding a strategy that may work correctly with the time series of the past but not so correctly for the future.

Thus, the contract amounts indicate that investors perceive a tendency for contract amounts to fall significantly as the PQI rises (Figure 2). There is a negative or inverse relation between option prices and the PQI. This result is attributed to the fact that the perception of risk and profitability comes into play as the PQI rises, prompting traders to adapt their strategies.

[23] With the backtesting technique it is posible to define the prices in the upper band, which means the market is overbought. If on the other hand it is in the lower band, this means the market is oversold.

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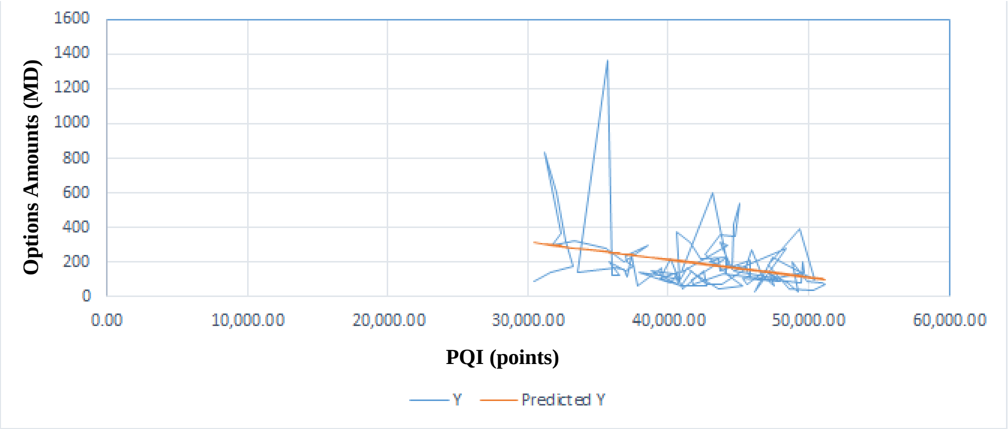

Figure 2. Trend of Options Contracts by PQI, 2010-2018
Source: created with data from MexDer and BMV.

Therefore, backtesting is undoubtedly useful as a process of simulating and testing the performance of a prediction model with time series and identifying possible failures going forward (Sobrepere Delgado, 2015, cited by López & Piedrahita, 2022). Nevertheless, this technique could reflect uncontrolled situations and lead to overestimating a strategy, which sometimes occurs easily.

Implications of the Options Investment Policy

There is a preference for having liquid assets and allocating wealth toward the financial sector, but this implies anticipating how to overcome the current crisis and the effects of economic policy in the real sector (Rodriguez & Venegas, 2012). It is important that investments in securities and debt, in an extraordinary way, see the possibility of facing risks through option contracts. This leads liquid resources to be hedged with the attractiveness of an option contract since it implicitly involves an underlying asset, offering more returns in the face of expected volatility.

Options can act as a risk transfer, giving a reward for assuming risk and volatility, as opposed to a random behavior of the "Random Walk" type (Caro et al., 1995: 163). There are moments of high volatility that cannot be solved with a single portfolio to face the risks. According to Bookstaber (1991), investors have a range of instruments that enable them to define their portfolios to hedge risk and market contingencies.

Defining a strategy for speculation is often important, especially when it is done with options. The design of the strategy leads to flexibility. Therefore, it depends on the requirements of margin payments, commissions, costs, and taxes. A strategy becomes relevant given the variety of options, puts,

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calls, exercise prices, and maturities (Mansell, 1992). It is the expectation of future price volatility or how the reference assets will move.

According to the results and the econometric specification, the estimations yield some behaviors of the option contracts concerning the PQI:

a) The options registered a high correlation with the stock market indices and functioned as an underlying asset, especially from 2010 to 2018, given the issuance of a group of large companies, such as América Móvil, Grupo México, and Femsa.
b) Contract amounts averaged $190 million in a month but peaked at $851 million. Excessive volatility in the series of option amounts resulted from pressures on large companies' balance sheets, safeguarding their liquid positions.
c) When running a regression of the option amounts (dependent variable) on the PQI (independent variable), it was observed that it resulted in volatility and efficient estimates. This was achieved using a GARCH (1,1) process and the quasi-maximum likelihood method. The standard errors and conditional variance were almost homoscedastic distributions over the period (volatility not so dispersed).

There is not a wide variety of options offered to clients in the market. Due to their high volatility, these contracts are linked to reference assets, such as the stock market index. Moretti (2015) quotes some authors on the fact that the business sector sometimes is unaware of how to take advantage of these instruments and the opportunities that occur when entering this market.

Conclusions

This study not only showed that market volatility affects investment decisions, but it was also possible to verify the persistence of this volatility in the options and the stock market index. This instability means that the GARCH process is valid in terms of parameter estimation and that it can be inferred that investment policies are viable in the case of options as a hedging instrument. It was possible to perform backtesting, which warns of investor perception, not only of the degree of volatility and risk but also that there is a tendency that as the PQI grows, the contract amounts register a significant drop. This tendency is due to a perception of risk and profitability at stake as the PQI rises, leading investors to adapt their strategies.

Stock-linked option contracts were the most attractive investment alternative in the face of stock index fluctuations. The GARCH process's results allowed for better parameters, and the volatility levels became satisfactory despite the contracts' instability. Indeed, the high volatility of the PQI did impact option investments, but it was still a good hedge against risks.

It was possible to obtain estimated parameters using the ARCH and GARCH methods for the conditional variance and the degree of expected volatility. The estimation of α and β was more satisfactory with GARCH, even though the errors do not have a normal distribution as these models presuppose. It was observed that the volatility and variance did not become constant (homoscedastic) to the extent that the underlying asset was the stock market index and the shares issued by the companies.

Running the regressions of the option amounts for the stock market index (PQI) identified the existence of volatility, which was not quite dispersed. The use of the GARCH process (1,1), applied to option contracts, whose underlying asset was the PQI of the Stock Exchange, made it possible to obtain more parameter estimates and predict volatility with reliable results and gave an idea of the risks involved. The ARCH method was useful when using the white noise test and the series of past lags in the residuals, which gave highly meaningful parameters.

The options market was generally volatile, and the contracts were preferred because they had an underlying financial asset. It would be useful for treasuries to be more aware of this, enabling them to have liquid resources and hedge against risks.

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