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Chicago and Mexico Futures Markets Asymmetries and Hedging

Asimetrías y cobertura en los mercados de futuros de México y Chicago

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Abstract

This work investigates the hedging performance of futures contracts in two asymmetric markets, peso/dollar traded at the Mexican derivatives market (MexDer); and dollar/peso traded in the Chicago Mercantile Exchange (CME). Value at Risk and Expected Shortfall enhanced by GARCH (1,1) modeling was applied. The left and right tails of the futures return series are examined, for both short and long positions. The period analyzed comprises from October 2016 to June 2017, partitioned in three subperiods; the results obtained for each market are compared, and finally their statistical validity is tested applying Kupiec backtesting. Overall, hedging in the CME is more effective, albeit the MexDer outperforms that market several times. However, all metrics (with and without GARCH modeling added) show important weakness below the 99 percent confidence level.

JEL Classifications: C58, F1, F39, G15, M21,

***Keywords**: Value at Risk, Expected Shortfall, GARCH, Peso futures hedging*

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Resumen

Este trabajo investiga el desempeño de cobertura de contratos de futuros en dos mercados asimétricos, peso/dólar negociado en el mercado mexicano de derivados (MexDer); y dólar/peso negociado en el Chicago Mercantile Exchange (CME). Aplicamos valor en riesgo y déficit esperado mejorado por el modelado GARCH (1,1). Se examinan las colas izquierda y derecha de las series de rendimientos de futuros, tanto para posiciones cortas como largas. El período analizado comprende de octubre de 2016 a junio de 2017, dividido en tres subperíodos; los resultados obtenidos para cada mercado se comparan, y finalmente su validez estadística se prueba aplicando backtesting Kupiec. En general, la cobertura en el CME es más eficaz, aunque el MexDer supera a ese mercado varias veces. Sin embargo, todas las métricas (con y sin el modelado GARCH agregado) muestran una debilidad importante por debajo del nivel de confianza del 99 por ciento.

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Palabras clave: Value at Risk, Expected Shortfall, GARCH, Peso futures hedging

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Introduction

Globalization has led during the last five decades to a significant growth in trade, real and portfolio investments which in turn have been accompanied with a greater use of currency transactions, albeit dominated by the dollar vis-a vis other national currencies. Growth, however, has been characterized by volatility of exchange rates. To prevent negative results in their operations, corporations, policy makers, investors and traders hedge their holdings, among other alternatives, with future contracts. Thus, currency hedge with future contracts has been reported widely in the financial literature.[1]

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1 Hedging (also known as covering) refers to any strategy employed to reduce the risk of undesirable price movements on holdings of any asset; the goal is securing a predetermined price (for the covered asset). Derivatives like futures, options and swaps are available for this purpose. Currency Futures examined in this paper are contracts to buy/sell a given currency for a specific price at a predetermined period in the future.

Various techniques have been used in previous research, attempting to estimate the efficiency of futures markets. A great deal of the literature has dealt with the optimum hedge ratio. Another strand of research has concentrated in estimating tails' risk attempting mainly to predict potential losses. Value at Risk analysis (VaR) models have been used for this purpose.

However, few studies compare the efficiency of converse currency future contracts offered by two different markets. This work examines the performance of peso/dollar contracts offered by the Mexican Derivatives Market (MexDer) vs. the dollar/peso futures offered by the Chicago Mercantile Exchange (CME), which, while reflecting symmetries between the U.S. and Mexican economies, also present important asymmetries in size, volume of trade, and maturity. Value at Risk (VaR) and Expected Shortfall (ES) methodologies were used, enhancing them by incorporating GARCH modeling. Moreover, these methodologies integrate the trading position, distinguishing between downside and upward risk.

Concretely, the objective of this paper is to analyze, contrast and determine which of those metrics, applied to both markets, yield better and statistically robust estimates about the currency coverage with the futures pinpointed above. The hypothesis is that it is possible to obtain greater accuracy estimating potential losses by applying ES under a GARCH approach, with different levels of confidence (90%, 95%, 97.5% and 99%). The hypothesis also includes that hedging in the CME leads to a better hedging results than those obtained in the MexDer. The period of analysis considers from October 2016 to June 2017.

Historically, México has been associated with Canada and the United States conforming the North American Free Trade Agreement, NAFTA (1994-2020) and has now entered a renewed regional integration agreement again involving the United States, Mexico and Canada, (UMSCA), starting on July 1, 2020. However, it is important to underlie the fact that Mexico's economy is less developed than its counterparts in the agreement, revealing severe economic and institutional differences among these countries.

Table 1 summarizes existing asymmetries in economic level between Mexico and the United States and the relative importance of the stock market in both countries. The Mexican economy amounts to only 5.53% of the U.S. gross national product; similarly, Mexico's GDP/capita amounts to US$10,292 thousand dollars which is 19.3% of the U.S. GDP per capita (US$53,336 thousand dollars).

Table 1

"Asymmetries between United States and Mexico, 2017
(billions of U.S. dollars)"

COUNTRY	GDP	GDP PER CAPITA	"TOT STOCK MKT CAPITALIZATION"	TOTALSTOCK MKT CAPITAL GDP
United States	19,485. 394	53,336	31,774.59	163.01%
Mexico	1,150.89	10,292	417.021	36.24%
Mexico/US	5.53%	19.30%	1.31%	

Source: World Bank National Accounts data, and OECD National Accounts data, 2020, and: https://siblisresearch.com/data/us-stock-market-value/ https://www.indexmundi.com/facts/mexico/market-capitalization-of-listed-companies

More striking is the difference regarding stock market capitalization. Total stock market capitalization in the U.S.[2] in 2017 reached $31,774.585 billion dollars, that is 163.01% in relation to GDP; in the case of Mexico total market capitalization during the same year was only $417.021 billion dollars, 1.31% in relation to the U.S. market size, and only 36.24% in relation to its own GDP. According to these indicators, financial deepening is rather low in Mexico which suggests a restricted performance of its financial markets, like in the case of the futures markets compared with the operations of the CME.

In this respect, our research contributes to the financial literature in two ways: 1) extending the financial literature by examining the performance of futures in two asymmetric economies characterized by markets, of different levels of development and offering a converse underlying asset; and, 2) analyzing practical alternative tools, sanctioned by regulating authorities, frequently used by market players in their decisions concerning estimations of currency coverage with futures of two economies linked by trade and financial activities facing significant economic-financial challenges. Moreover, it is important to recall that Mexico is the 15th world economy (World Bank 2020), while the Mexican peso currently ranks eight in the world regarding global liquidity, behind the USD, EUR, JPY and GBP, and its

2 It includes market capitalization of all U.S. based public companies listed in the New York Stock Exchange, Nasdaq, and OTCQX U.S. Market: https://siblisresearch.com/data/us-stock-market-value/

most popular currency pairing is the United States Dollar (Forex Trading Academy, 2020).

The paper is structured as follows. After the introduction, the second part presents a review of the literature. The third section describes the data and pre-estimation statistical analyses. The fourth section deals with the Value at Risk, Expected Short Fall, and GARCH econometric models. The fourth part corresponds to empirical application and analysis of results. The fifth and final section presents the conclusions.

1. Related research

As previously mentioned, foreign exchange risk has become more and more important. The financial markets have responded either enhancing traditional hedging instruments, or else creating new derivatives for this purpose. The volatility of markets, along with a search for tools to manage risk, have led to serious academic research and to the design of new financial instruments. In this section, some studies related to the use of VaR and Expected Short Fall applications adjusted by GARCH modeling are reviewed. GARCH modeling is important to overcome homoscedasticity assumption problems, which are ignored in many studies. It is important to acknowledge that VaR and ES have been endorsed by international and local regulation authorities. The complexity of other sophisticated models has limited their application, particularly in emerging markets.

Various studies confirm the benefits of hedging strategies with futures by applying VaR analyses extended with GARCH modeling**.** Among some earlier works there must be mentioned Burns (2002), Yamai and Yoshiva (2005) and Mazin and Janabi (2006). Burns (2002) compares VaR estimates using univariate GARCH models. His study comprised a sample of the S&P index over a period of nearly 70 years of daily returns. His evidence shows that GARCH estimates are superior to the other methods in terms of the accuracy and coherence.

Yamai and Yoshiva (2005) illustrate that tail risk of VaR can cause serious problems in certain cases; expected shortfall can serve as an alternative. The authors analyze concentrated credit portfolios, and foreign exchange rates under market stress. They show that expected shortfall requires a larger sample size than VaR to provide the same level of accuracy. Mazin and Janabi (2006) deal with foreign trade risk for the case of the Moroccan Dirhamt, considering proper adjustments for the illiquidity of both long and short trading positions. They employ value at risk (VaR) to assess risk and they deliver proactive practical approaches to manage foreign-exchange trading risk exposures.

A more recent work by Wang, Wu, Chen And Zhou (2010) employ extreme value theory (EVT). According to their findings, the expected shortfall cannot improve the tail risk problem of value-at-risk (VaR). The evidence of back testing indicates that EVT-based VaR values underestimate the risks of exchange rates such as USD/CNY and HKD/CNY, most likely caused by the continuous appreciation of CNY against USD and HKD. However, compared with VaR values calculated by historical simulation and variance–covariance method, VaR values calculated by EVT can measure risk more accurately for the exchange rates of JPY/CNY and EUR/CNY.

In turn, Ben Raheb, Ben Salha, and Ben Rejeb (2012) empirically test four Value-at-Risk simulation methods, namely, Variance-Covariance, Historical Simulation, Bootstrapping and Monte Carlo simulation. Their study includes three currencies and four currency portfolios in the Tunisian exchange market. The data covers the period from 1999 to 2007. Independently of the technique applied, the Japanese Yen seems to be the riskiest currency. In addition, as expected, diversification reduces exchange rate risk. Results based on these tests suggest that the traditional Variance-Covariance is the most appropriate method.

In another work, Nadarajah (2014) also find some limitations on value at risk and decide to apply *expected shortfall* to overcome them. They make an important contribution reviewing estimation methods of over 140 references about expected shortfall.

A frequent research theme deals with the relationship between exchange rates and stock markets. This is the approach followed by Reboredo, Rivera-Castro, and Ugoline (2016)**.** They extend the analysis of foreign exchange risk examining downside and upside risk spillovers from exchange rates to stock prices and vice versa for a set of emerging economies. Dependence is determined using copulas and estimating downside and upside value-at-risk and conditional value-at-risk. Findings reveal a positive relationship between stock prices and currency values in emerging economies with respect to the US dollar and the euro, with downside and upside spillover risk effects transmitted both ways. Furthermore, they also find asymmetries in upside and downside risk spillovers and asymmetric differences in the size of risk spillovers with the domestic currency values against the US dollar and the euro.

In a more recent work, Burdorf and van Vuuren (2018) recognize that Expected Shortfall has been imposed by regulatory authorities to overcome the limitations of VaR (it is neither sub-additive nor coherent). However, VaR is still needed to estimate the tail of conditional expectation (the ES). These two risk measures behave very differently during growth and recession periods in developed and emerging economies. Using equity portfolios assembled from securities of the banking and retail sectors in the UK and South Africa, historical, variance-covariance and Monte Carlo approaches are used to determine VaR (and hence ES). The results are back tested and compared, and normality assumptions are tested. The empirical evidence shows that the results of the variance covariance and the Monte Carlo approaches are more consistent in all environments in comparison to the historical outcomes regardless of the equity portfolio considered. The industries and periods analyzed influenced the accuracy of the risk measures; the different economies did not.

Following this trend of studies, Su and Hung (2018) utilize seven bivariate (GARCH) models to forecast the out-of-sample VaR of 21 stock portfolios and seven currency-stock portfolios with three weight combinations. The seven models are constructed by four types of bivariate variance-covariance specifications and two approaches of parameters estimates. The four types of bivariate variance-covariance specifications are the constant conditional correlation, asymmetric and symmetric dynamic conditional correlation and the BEKK model; the two include the standard and non-standard approaches. Empirical results show that, regarding the accuracy tests, the VaR forecast performance of stock portfolios varies with the variance-covariance specifications and the approaches of parameters estimate, whereas it does not vary with the weight combinations of portfolios. Conversely, the VaR forecast performance of currency-stock portfolios is almost the same for all models and still does not vary with the weight combinations of portfolios.

Tabasi, Yousefi, Ghasemi and Tamošaitienė (2019) estimate market risk in the Tehran Stock Exchange; they employ Conditional Value at Risk and Expected Shortfall. Extreme Value Theory is used to measure risk more precisely. Also, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are employed to model the volatility-clustering feature, as well as to estimate the parameters of the model, The Maximum Likelihood method is also employed. The evidence reveals that when estimating the model parameters, assuming a t-student distribution function delivers better results than the normal distribution function. Finally, Monte Carlo simulation is employed for back-testing.

Also, related to recent trends in VaR/ES research, Paton, Zeigel, and Chen (2019) make use of contemporary statistical decision theory to surmount the problem of "elicitability" for ES by *jointly* modeling ES and VaR, which leads the authors to propose new dynamic models for these risk metrics. Estimations and inference methods are carried out for the proposed models; employing simulation they prove that their methods have good finite-sample properties. These models are applied to daily returns on four international share indices; the evidence confirms that the proposed new ES–VaR models outperform forecasts using GARCH or rolling window models.

Taylor (2019), using stock market indexes, advances a method for predicting ES corresponding to VaR forecasts produced by quantile regression models, methodology equivalent to maximum likelihood based on an asymmetric Laplace (AL) density. He allows the density's scale to be time-varying and shows that it can be used to estimate conditional ES. Thus a joint model of conditional VaR and ES by maximizing an AL log-likelihood is presented. Although this estimation framework uses an AL density, it does not rely on an assumption for the return's distribution. Taylor also uses the AL log-likelihood for forecast evaluation and show that it is strictly consistent for the joint evaluation of VaR and ES.

Most recently, Badaye and Narsoo (2020) present a novel methodology to explore the performance of several multivariate VaR and ES models in order to estimate the risk of an equally weighted portfolio of one minute intraday frequency observations for five foreign currencies; they employ the multiplicative component MC-GARCH model on each return series and by modelling the dependence structure using copulas. VaR and ES are forecasted for an out-of-sample set using Monte Carlo simulation. Concerning VaR forecasting performance, back-testing results indicated that four out of the five models implemented could not be rejected at five per cent level of significance; further evaluation of the ES forecasting models revealed that only the Student's *t* and Clayton models could not be rejected, which heightens the importance of selecting an appropriate copula modeling for the dependence structure.

Another research using intraday data is the work by Meng and Taylor (2020). To attain further information about the tail behavior of five stock indexes returns, as well as concerning five individual corporate shares returns, the authors develop joint scoring functions for VaR and ES which allow them to estimate two risk measures based on intraday data. Meng and Taylor focus on the intraday range, namely the difference between the highest and lowest intraday low prices. To alleviate the challenge of modelling extreme risk measures, the authors propose using the intraday low series. Based on a theoretical result applying Brownian motion they show that a quantile of the daily returns can be estimated as the product of a constant term and a less extreme quantile of the intraday low returns; this is defined as the difference between the lowest log price of the day and the log closing price of the previous day. Then, they employ the VaR and ES estimates of the intraday low returns to estimate the VaR and ES of the daily returns. Meng and Taylor provide empirical support for the new proposals using data for five stock indices and five individual stocks.

Concerning Latin America and Mexico the literature reports few studies, none is related with exchange rate coverage. Alonso and Arcos (2006) employ various parametric and nonparametric methods for calculating the VaR metric for a portfolio of 7 Latin American markets; they employ EWMA and TGARCH models, the most suitable models for 95% confidence levels, however, showing low performance taking a 99% confidence level.

Similarly, Vergara and Maya (2007) have a work on parametric and nonparametric GARCH models for stock returns belonging to the Colombian market; in their work they present applications of VaR and a multivariate GARCH model concluding that the modeling of the conditional distribution of returns corroborates the superiority of the estimation of these models over the conditional covariance matrix in the determination of gains obtained.

Finally, Ramírez and Ramírez (2007) focus their study on the analysis of VaR metrics applied to Mexican shares. de Jesús and Ortiz (2012) work with the CVaR model in conjunction with the theory of extreme values applying them to the stock indices of Brazil and Mexico, while Reyes and Ortíz (2013) use the M-VaRCH methodology (Value at Risk models and multivariate GARCH models) to analyze trinational portfolios from the NAFTA countries, Canada, United States and Mexico.

Summing up, research on risk associated with exchange rate and hedging strategies is very important. The use of VaR and CVaR show the potential losses that the foreign exchange market can incur in. Applying GARCH modeling to those metrics, enhances their precision and applicability. Regarding currency hedging, academic research has concentrated on other risk issues such as the determination of the optimal hedge ratio. The use of

VaR modeling has been rather limited, albeit highly sophisticated models have been designed for mature markets and developed economies.

VaR applications for emerging markets have mostly dealt with the impact of exchange rates on trade, and real and portfolio investments. Furthermore, research using high frequency intraday data is nonexistent in these markets due to the lack of information, as well as high costs. There are no concrete works about exchange rate hedging in Mexico. Therefore, this paper constitutes an important contribution on this matter. Moreover, this paper uses VaR metrics to compare hedging efficiency between two markets: one fully developed, and the other an emerging market; hedging is estimated in the dollar/peso offered by the CME of Chicago vis a vis the peso/dollar futures offered in the MexDer. The final econometric Var and ES include GARCH modeling to overcome erroneous homoscedasticity assumptions assumed in many studies.

3. *Data and pre-estimation statistical analyses*

3.1. *Data and period studied*

A careful research strategy considering the big differentials between the MexDer and the CME was undertaken. Contract characteristics are similar. However, the CME is the largest futures market globally and its operations began in the nineteenth century. The MexDer, on the contrary, is a small market from an emerging economy; after some transitional issuing of some forward-warrant assets, the market finally began operations on December 15, 1998, trading peso/dollar futures.

Although trading contracts follow similar norms than other markets, besides the differences in size and maturation, the big difference so far is the size of each contract. In Mexico, each futures contract covers a lot of 10,000 U.S. dollars; in the CME each futures contract covers a lot of 500,000 Mexican pesos about 22,230 U.S. dollars. Futures in each market are subject to the volatility of both currencies, but the dollar is the dominant currency.

The period of analysis includes from October 2016 to June 2017. Data for the CME and the MexDer was gathered from Bloomberg; exchange rate was obtained from Banxico (Mexico's Central Bank). For this research, it was considered a nine months cycle subdivided in three subperiods. The lapses between these partitions are: The first sub period (ex-ante) includes from October to December 2016, it analyzes the behavior of hedging prior a lapse of some stress; the second period examines the problem during a volatility

Table 2			
Exchange Rate Pressure Periods			
Subperiods			
Peso Futures in Chicago			
	FROM	TO	
EXANTE_FMXP PERIOD	OCT¨-16	DEC-16	PERIOD PRIOR EXCHANGE PRESSURE
AMIDTS_FMXP PERIOD	JAN¨-17	MAR¨-17	PERIOD AMIDTS EXCHANGE PRESSURE
EXPOST_FMXP PERIOD	APR-17	JUN¨-17	PERIOD AFTER EXCHANGE PRESSURE
Dollar futures in Mexico			
EXANTE_FDOLLAR PERIOD	OCT¨-16	DEC-16	PERIOD PRIOR EXCHANGE PRESSURE
AMIDTS_FDOLLAR PERIOD	JAN¨-17	MAR¨-17	PERIOD AMIDTS EXCHANGE PRESSURE
EXPOST_FDOLLAR PERIOD	APR-17	JUN¨-17	PERIOD AFTER EXCHANGE PRESSURE

Source: Prepared by authors with data from Blomberg and Bank of Mexico

sequence, from January to March 2017, impacted by tensions caused to the Mexican economy due to decreasing and unstable oil prices (Mexico's second largest export), as well as a shaky exchange rate; the third (Ex-post period) comprises April to June 2017, which aims to examine post-stress futures behavior in both the Mexican and Chicago futures markets. This approach allows us to analyze in dept the performance of both markets. Table 2 shows these subperiods.

3.2. Stationarity Analysis and Basic Statistics

Daily closing prices were used to calculate the logarithm of prices returns. All econometric analyses performed in this paper used these returns.

$$r_i = \log\left[\left(\frac{p_i}{p_j}\right)\right] \qquad (1)$$

Where $p_i > p_j$

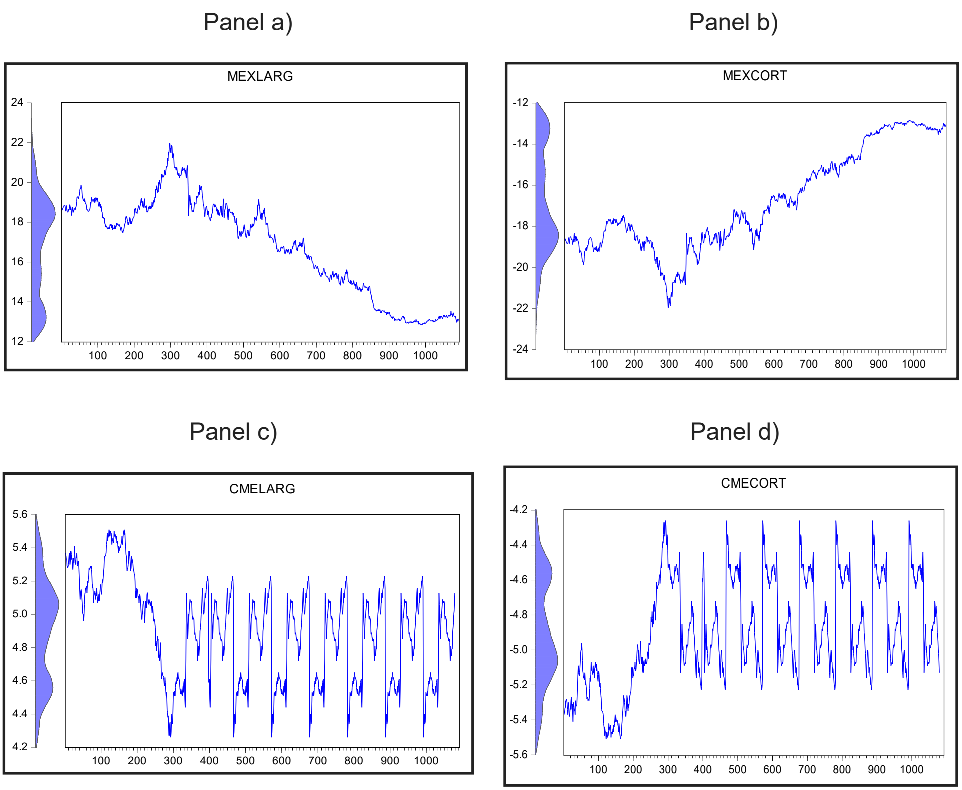
To ensure well-founded answers to the hypothesis, first the stationarity of the series was tested, applying the ADF test. The t-Student test was also carried out to reinforce the results of the stationarity of the series. Normality was tested employing the Jarque-Bera test (Jarque-Bera, 1987).

To the above described tests, the ARCH LM test for heteroscedasticity was added, for one, two, three and four lags. Akaike and Schwartz criteria were used to determine the minimum of lags that the model may include, which is expected to be a GARCH (1,1). The models ARCH and GARCH were applied with intercept and a moving average mean; the results were examined following the above-mentioned criteria.

In relation to the analysis and adjustment of volatility, the standard deviation in statistical terms is a measure of the rigor of random changes, generally unpredictable variations in the profitability or price of a title. Figures 1 and 2 show the historical behavior of spot and future prices and logarithmic returns for both the MexDer and the CME.

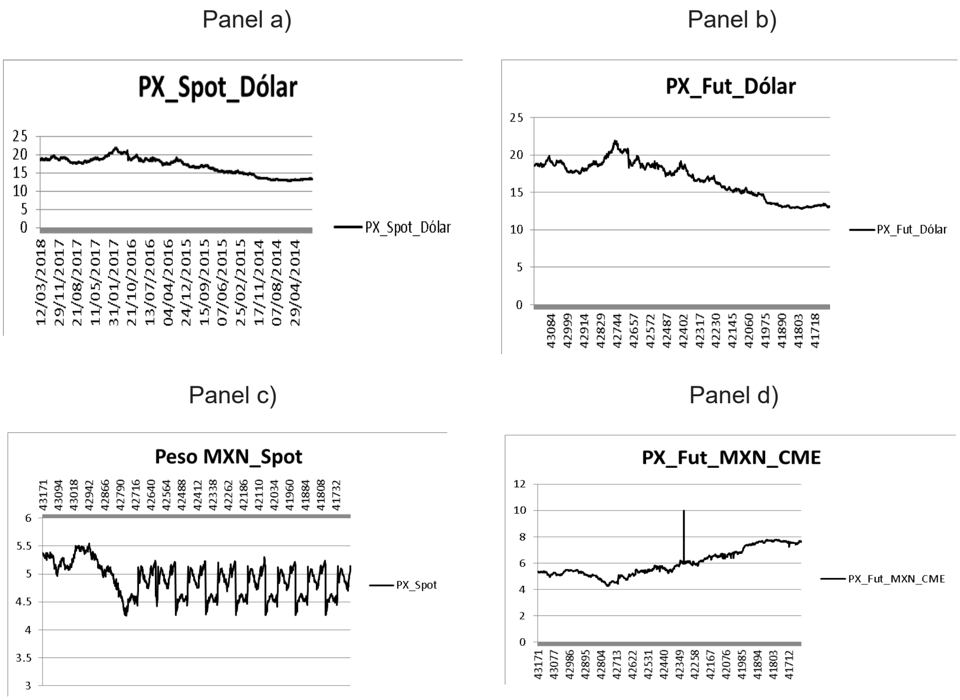
The asymmetrical and characteristic volatility clusters of the logarithmic returns series derive from the size of the impacts on prices and returns in certain periods. Particularly, market instabilities and bad news

Figure 1. Behavior of Mexican and U.S. futures prices series



Source: Prepared by authors with logarithmic returns from data on the futures prices from Bloomberg and Banxico.

Figure 2. Behavior of Mexican and U.S. futures returns series



Source: Prepared by authors with logarithmic returns from data on the futures prices of MexDer and CME

increase volatility. At first glance, it would appear that the series are non-stationary (the mean being a function of time and non-constant variance).

Table 3 presents the basic statistics of the full sample series. It can be observed that the mean values for both markets and for future prices and their returns are positive. Regarding the price series, the variance in the MexDer is greater than the variance of the CMD. Yet, the logarithmic return series reveal the opposite behavior; CME's standard deviation is larger.[3] Concerning kurtosis, Table 3 highlights the fact that all return series are high peaked. As far as asymmetry is concerned, all series are asymmetric, skewed to the left.

3 Econometric results reported in Tables 3 and 4 were obtained employing E-View 10.0.

Finally, the Jarque Bera statistics confirms that all series are non-normal. The sharp differences in the statistical behavior of these market can be attributed to the fact that future lots are traded in currencies of different value, reflecting therefore the instability of the peso in the MexDer. However, this behavior also suggests the presence of market segmentation among these two neighboring countries; apparently, participants (hedgers) in these markets belong to well differentiated groups; most likely, few participants operate in both markets. The identified differences also unveil opportunities for price arbitrage; the dollar price in the MexDer and its equivalent in pesos in the CME most likely present temporary price disequilibria creating opportunities for spatial arbitrage.[4]

The results of the Dickey Fuller Augmented Unit Root (ADF)[5] indicate that the normal (raw) series are non-stationary, since the test value is

Table 3

Basic Statistics of prices and logaritmic return series of the MexDer and CME

Market	Futures	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
Futures Prices							
MexDer							
	Dollar Futures	16.8449	2.4040	-0.2712	1.907	66.852	-13.166
	Dollar Spot	16.8401	2.4094	-0.2654	1.898	67.274	-19.353
CME							
	MXP Futures	5.9999	1.0064	-0.4909	2.102	37.557	-23.394
	MXP Spot	4.8992	0.3004	-0.1028	2.106	37.849	-31.623
Logaritmic Return Series							
Market	**Returns**	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**ADF**
MexDer							
	Dollar Futures	0.00002	0.0083	-0.1363	3.657	22.739	-2.864
	Dollar Spot	0.00003	0.0001	-0.0448	4.827	150.243	-2.864
CME							
	MXP Futures	0.00014	1.0984	-0.1291	8.064	1154.824	-2.864
	MXP Spot	0.00014	1.0918	-0.1209	9.449	1870.436	-2.854
95% C.V.						5.99	-3.96

Source: Prepared by authors with futures and spot prices. Bank of Mexico and Bloomberg.

4 Taking advantage of the lower price in one market to sell at the higher price in the other market.

5 Dickey and Fuller (1979).

Table 4

HETEROCEDASTICITY TEST				
Arch Test				
Criteria	**Dollar Futures**	**Spot Dollar**	**MXPFutures**	**Spot MXP**
Akaike info criterion	-8.7058	-8.7455	-6.7534	-6.9092
Schwarz criterion	-8.6921	-8.7270	-6.7349	-6.8907
Hannan-Quinn criterion	-8.7006	-8.7385	-6.7464	-6.9022
GARCH Test				
Akaike info criterion	-8.7791	-8.8560	-6.7734	-6.7903
Schwarz criterion	-8.7607	-8.8328	-6.7449	-6.9672
Hannan-Quinn criterion	-8.7721	-8.8472	-6.7564	-6.9815
ARCHLM 1 Test				
Akaike info criterion	3.9088	3.9640	9.1179	6.7677
Schwarz criterion	3.9180	3.9732	9.1271	6.7770
Hannan-Quinn criterion	3.9123	3.9675	9.1214	6.7712

Source: Prepared by authors with futures and spot prices. Bank of Mexico and Bloomberg.

smaller than the critical value (-3.96); however, the logarithmic return series are stationary according to the same criterion. This is substantial from the point of view of coverage, since non-stationary series can lead to spurious regressions results and therefore invalidate the coverage estimate.

Figures 2, and 3 and Table 2 confirm that the spot and future time series of the Mexican and Chicago derivative markets are non-normal; These findings justify the decision to test stationarity applying the unit root Augmented Dickey Fuller test. The results are presented in Table 4. We apply this test for price levels and first differences without intercept and trend. The test confirms that the series of logarithmic returns are non-stationary, as shown in Table 2.

The tests ARCH 1, GARCH (1.1), and ARCHLM 1 were carried out. Models were selected according to the Akaike, Schwartz and Hannan, criteria. The decision rule indicates to choose the model with the lowest numerical values which in this case corresponds to the GARCH (1.1) model (Table 3).

4. VaR and ES econometric modeling

4.1 Value at Risk (VaR)[6]

The VaR of a portfolio of financial futures contracts is defined as the maximum expected loss that an investor will face over a period of time given a confidence level α, (usually 95%, 97.5% and 99%), when investing, anchoring or liquidating positions in the portfolio due to unforeseen movements affecting market factors such as exchange rates, interest rates, prices of financial assets. Likewise, this metric is used by regulators to procure control of the operations carried out by financial institutions to establish standard capital requirements measures of financial institutions.

Statistically, VaR is defined as the probability that changes in the portfolio value will not exceed the maximum expected loss over a specified period of time for a given confidence level; Let

$$\Pr(\Delta P \leq -\mathrm{VaR}\alpha) = \alpha \tag{2}$$

Where, ΔP represents changes or losses in the value of the portfolio. Another way to estimate the VaR of a portfolio is calculated by finding the inverse function of the cumulative distribution of risk factors. That is, a space of probability is fixed (Ω, F, P) where Ω represents the sample space or set of possible outcomes, F is a σ algebra representing measurable events, P is a measure of probability, and X is a random variable representing the investment portfolio losses and earnings during a given period of time.

$$F_X(x) = \Pr(X \leq x) \tag{3}$$

Where $F_X(x)$ is a continous function with a density function $f_X(x) > 0 \; \forall \; x \in R$ $F_X(x)$ is strictly growing $\forall \; x \in R$, so that $\exists \; F_X^{-1}(x)$, with $0 < x < 1$. Hence the VaR of v.a. X is determined by the percentile α of the profit and loss distribution $F_X(x)$, this is,

$$VaR_\alpha = - F_X^{-1}(x) \tag{4}$$

6 It is fair to acknowledge that although this metric has a long-standing background, a formal practical model was advanced by JP Morgan in the 1990's. The metric has also become very popular in teaching and research to a great extent due to a text published by Jorion (1996).

Additionally, let the set $M \subset L^0(\Omega, F, P)$ representing the set of random variables of financial risk mapping from M to R, so that ρ: M → R, with X v.a. → ρ (X) contained within the confidence interval ϵ (0,1). So that VaR is defined for a certain confidence level α, so probability of losses X do not be greater than (1-α), therefore,

$$VaR = mín\,\{x \in R: P(X > x) \leq 1{-}\propto\} \qquad 5)$$

$$= mín\,\{X > x: F_{X\geq} \propto\} \qquad (6)$$

This provides the return that is exceeded with a probability of $(100 - \propto)$ per cent. However, two portfolios may have the same VaR value but with different potential losses. This is because the VaR does not calculate losses beyond the 100% percentile. This deficiency is mitigated by estimating an additional performance metric, that is, the Conditional Risk Value (CVaR) or Expected Shortfall (ES) described below. The Value at Risk is estimated by applying i, with αi, with i = 1%, 2.5%, 5%, and 10%. In our study the performance metric used corresponds to the percentage reduction in the VaR-GARCH (throughout this paper it will be called VaRG), which measures the percentage VaR-GARCH (applying the GARCH model) of a hedged portfolio compared to the VaR-GARCH of an uncovered portfolio, this applies to both VaR and ES; the Cotter and Hanly (2006) efficiency coefficient was slightly modified to include GARCH modeling. Our modified version is:

$$VaRG = 1 - \left\{\frac{\boldsymbol{VaR\,(GARCH)_{i\%}\,hedged\,portfolio}}{\boldsymbol{VaR(GARCH)_{i\%}\,unhedged\,portfolio}}\right\} \qquad (7)$$

VarG = the percentage reduction in the VaRG of the hedged portfolio as compared to the unhedged portfolio. If future contracts fully eliminate risk VaRG = 1, whereas, if VaRG = 0 futures contracts do not reduce risk. Therefore, let x be a result of applying the metrics, then $\left[x \in R \;\middle|\; 0 \leq x \leq 1\right]$, hence, a greater x indicates a better performance of the coverage. The same applies for the ES metrics. VaRG was estimated using various confidence levels, α = 10%, 5%, 2.5%, y 1%.[7]

Several criticisms have been generated towards the VaR model since it shows instability if there is no normal distribution of losses, as empirical evidence indicate. Thus, coherence is only based on the standard deviation of normal distributions on asset returns; under the assumptions of normal distribution the VaR is proportional to the standard deviation of the instrument returns (Reyes and Ortiz, 2013). This leads us to choose ES which is a coherent metric since it provides an estimator not only of the probability of loss, but also of its magnitude.

4.2 Conditional Value at Risk (CVar), or Expected Shortfall (ES)

The CVaR, or ES measures the average loss conditioned to the fact that VaR has been exceeded. Such metric provides, as mentioned, coverage with an estimator not only of the probability of loss, but also of the magnitude of a possible loss.

1. This means that managing risk using VaR can be inefficient to capture the effects of diversification which reduces portfolio risk
2. Uryasev and Rockafeller (2002) (2002) responded to this VaR problem advancing Conditional Value at Risk (CVaR), also known as Expected Shortfall (ES). When the distribution of profit and loss follows a normal distribution, then it should be used.

$$\mathrm{ES} = \int_{-\infty}^{t} (\mathrm{t} - \mathrm{R})^{1}\, \mathrm{dF(R)} \tag{8}$$

$$(ES)_{\varphi}(X) = E\left[-X \middle| -X \le VaR_{\varphi}(X)\right] = \frac{e^{\frac{-q^2\varphi}{2}}}{\varphi\sqrt{2\pi}} \tag{9}$$

It is an alternative risk measure to partially amend the deficiencies presented by VaR. CVar is often referred to as the expected deficit or Expected Shortfall, ES.

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7 The formula generalizes for portfolios of n assets. Our portfolio comprises only one asset in each market: the dollar in the MexDer and the Peso in the CME. The hedged portfolio refers to the asset protected with a futures contract; the unhedged portfolio simply holds the original asset unhedged.

For a X, let $E(|X|) < \infty$ and its distribution function , the Expected Shortfall of a given confidence $\alpha \in (0,1)$ can be defined as,

$$(ES) = \frac{1}{1-\alpha}\int_0^1 q_u(F_X)du \ldots\ldots \qquad (10)$$

Where $q_u(F_X) = F_X(u)$ is a quantile function F_X, thus, the relation between VaR and y ES is,

$$CVaR\ (ES) = \frac{1}{1-\alpha}\int_0^1 VaR(F_X)du \ldots\ldots \qquad (11)$$

The expected excess measure is a coherent risk measure based on the expected value of potential losses that exceeds the VaR level. This robust risk measure has been studied independently and defined in different ways by several authors in recent years. The main names or variants adopted by this risk measure are as follows: Tail Conditional Expectation (TCE), Worst Conditional Expectation (WCE), Tail Mean CVaR, Mathematical Conditional Expectation of VaR Losses, Expected Shortfall (ES), Conditional Value at Risk (CVaR) (de Jesús 2008).

In statistical terms, the ES is based on a continuous distribution whose random variable measuring changes in portfolio value losses can be defined as: the mathematical conditional expectation of losses that have exceeded the VaR level,

$$ES\alpha(X) = -E\big(X \big| X \le VaR(X)\big) \qquad (12)$$

As in the performance metric presented in eq. (7) to evaluate coverage performance in the VaRG model, the coefficient to include GARCH assessment was modified. In this model, the coefficient corresponds to the percentage reduction in the ES, under the alphas considered in the VaRG; the modified Cotter and Handly (2006) efficiency coefficient, to include GARCH modeling is:[8]

8 See supranote 4.

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$$ESG = 1 - \left\{\frac{ES(GARCH)_{i\%}\ hedged\ portfolio}{ES(GARCH)_{i\%}\ unhedged\ portfolio}\right\} \quad (13)$$

So, if a position in CME is found to have a higher VaRG but a lower ESG than MexDer futures, that indicates that the volatility of futures in CME is higher in normal market situations, but in extreme situations the MexDer futures have higher volatility.

4.3. GARCH Modeling

The use of GARCH (p,q) models has become widespread to explain the variance in time. In general, GARCH models assume that conditional variance is affected by their past events. The advantage of these models over the original ARCH models (p) is that GARCH models allow to capture persistence of volatility (presence of volatility clusters). In fact, regarding exchange rates, several papers in the financial literature deal with the issue of optimal coverage using multivariate GARCH models to generate optimal hedge ratio (Kroner and Sultan, 1993). However, the performance of multivariate GARCH models has been poor when used to generate forecasts over longer coverage horizons (Brooks *et al*., 2002), which is not the case of our partitions.

The GARCH model we employ is the Vector GARCH model (1,1) proposed by Bollerslev (1986). This model has been also used to generate optimal hedge ratio by Baillie and Myers (1991) and Brooks and Chong (2001). This models the conditional mean and variance equations as follows:

$$r_{st=}\ \mu_s + \varepsilon_{st} \quad (14)$$

$$r_{ft=}\ \mu_f + \varepsilon_{ft} \quad (15)$$

$$\binom{\varepsilon_{st}}{\varepsilon_{ft}}\omega_{t-1} \sim N(0, \sigma_t^2) \quad (16)$$

$$\sigma_{st}^2 = \gamma_s + \alpha_s \varepsilon_{s,t-1}^2 + \beta_s \sigma_{s,t-1}^2 \quad (17)$$

$$\sigma_{ft}^2 = \gamma_f + \alpha_f \varepsilon_{f,t-1}^2 + \beta_f \sigma_{f,t-1}^2 \quad (18)$$

$$\sigma_{sft}^2 = \gamma_{sf} + \alpha_{sf} \varepsilon_{s,t-1}^2 \varepsilon_{f,t-1}^2 + \beta_{sf} \sigma_{sf,t-1}^2 \quad (19)$$

where,

r_{st} y r_{ft} = spot and futures' returns, respectively,

ε_{st} y ε_{ft} = residuals representing innovations in the spot and futures prices, respectively,

Ω_{t-1} = the information set at time t-1,

σ^2_{st} and σ^2_{ft}, = variance of spot and futures, respectively, and

σ_{sft} = ε_{st} and ε_{ft} covariance.

However, this model is restricted to the diagonal arrays α and β, so only the upper triangular portion of the variance-covariance matrix is used. This means that the conditional variance depends on past values themselves and the past values of square innovations in returns. This reduces the number of parameters to nine (each of the α and β has three elements). This is subject to the requirement that the variance-covariance matrix be positively defined to generate positive elements of coverage. Let

$$r_{st=}\ \theta_{s0}\ +\sum_{j=1}^{J} r_{s,t-j}\,\theta_{sj} + \varepsilon_{st}, r_{ft} = \sum_{k=1}^{K} \theta_{fk}\ + \varepsilon_{ft} \qquad (20)$$

$$\begin{pmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{pmatrix} \Big| \,\Omega_{t-1} \sim N(0, \sigma_t^2) \qquad 21)$$

$$\sigma^2_{sft} = \rho\sigma_{st}\sigma_{ft} \qquad (22)$$

where, j,k = 1 for the GARCH (1,1) model; $\gamma, \alpha\ and\ \beta$ are positive, and $\alpha_i + \beta i \leq 1, for\ i =\ s, f$. The conditional mean follows an autoregressive process. The correlation coefficient ρ equation (22) is a constant. One advantage of this model is that it consists of a positive semi-defined matrix, subject to positive conditional variances, which means that the variance-covariance matrix is positive or non-negative. When using this method, the results are used to build hedging portfolios where $+r_s - h * r_f$ is the short hedge, y is the long hedge, r_s and r_j are the spot and futures returns respectively, and, $h*$ is the estimated hedge.

4.4. Backtesting or Kupiec proportion of failures test

Kupiec (1995) proposed a test intended to quantify whether the significance level proposed by the VaR metric is consistent with the proportion of failures that the model presents, i.e., it is a question of confirming whether the model is appropriate considering how many times the losses or gains exceed the VaR (failure rate) in the period under consideration. The hypothesis of this paper assumes that the failure ratio is the same than the significance level of the model. The test verifies that the probability of the number of failures is equal to "x" over a sample "n", considering a binomial distribution,

$$P(x; n; p^*) = \binom{n}{x}(p^*)(1-p^*)^{n-x} \tag{23}$$

The probability of failure (p^*) of the VaR metrics is estimated applying a maximum likelihood process, a likelihood ratio (LR). Finally, logarithms of a binomial distribution are gathered, and this function is maximized with respect to the estimated probability (p^*). Once the LR estimator is obtained, a statistical contrast is established between the theoretical and estimated probabilities (p^* *and* $\tilde{p}$, respectively). The assessment of significance is carried out with the maximum likelihood ratio, from the logarithm of the probability distribution applied for each of these probabilities; the likelihood ratio defined as:

$$LR_{UC} = 2\left[\frac{(p^*)^x(1-p^*)^{n-x}}{(\tilde{p})^x(1-\tilde{p})^{n-x}}\right] \tag{24}$$

The LR test represents a Chi- square distribution with one degree of freedom.

5. Empirical Analysis

5.2. Empirical Applications

Hitherto we have established the statistical characteristics of the price and return series and determined the GARCH (1,1) model appropriate to estimate the volatility of the logarithmic returns of spot and futures series of the MexDer and the CME. The econometric models for estimating the VaRG and ESG models are presented. Aiming at the greatest precision, in this section we report and compare the evidence obtained using confidence levels of 90%, 95%, 97%, and 99%.

Table 5 shows the results of coverage performance for each metric used, each of the partitions, hedging strategies (short and long), and each of the confidence levels considered. The performance of hedging strategies for each of the metrics involves the generation of many contrasting outcomes, which allows to stress some key differences.

First, it is important to stress that both the hypotheses assumed are confirmed. In all situations the ES-GARCH model outperforms the VarGARCH model. Its estimates are more precise at all confidence levels, for both the Mexican Market and the CME, again, for both the short and long positions. Similarly, the Chicago market shows a better performance than the Mexican market in 28 out of 48 total hedging alternatives. Table 5 also shows that for all (short and long) positions (short and long) at 97.5% and 99.00% confidence levels the CME performance surpasses the Mexican performance applying the ES-GARCH model. At lower confidence levels the VaR-GARCH and ES-GARCH models interchange some results.

Another interesting outcome is the practically nil efficiency of both methodologies in both markets for confidence levels of 97.5% and below applying the VaR-GARCH method; very frequently hedging is in the 70.0% and even lower mark. This problem is almost inexistent applying the ES-

Table 5

"Metrics under GARCH approach: VaRG (VaR-Garch) y ESG (Expected Shortfall-Garch)

		VaRG = 90%,	VaRG 95%,	VaRG 97.5%	VaRG 99%	"VaRG90%	VaRG95%	VaRG 97.5%	VaRG 99%
MexDer Dollar futures									
	EX ANTE	71.19	74.39	84.59	90.43	86.66	97.78	91.57	92.43
Short	AMIDTS	70.25	76.73	79.73	86.82	85.23	95.48	89.25	91.82
	EX POST	68.49	77.27	90.03	80.87	78.34	97.28	90.27	82.87
DEUA	EX ANTE	74.12	77.33	71.19	78.43	88.72	88.43	93.72	94.43
Long	AMIDTS	69.84	71.19	74.91	81.82	85.28	92.82	91.23	97.28
	EX POST	69.69	80.91	73.96	77.87	77.36	92.87	89.24	95.87
CME Peso Futures									
MXP	EX ANTE	79.53	90.96	75.91	85.52	91.27	93.79	93.41	95.89
Short	AMIDTS	76.26	75.91	68.59	80.37	86.29	91.26	89.35	93.26
	EX POST	71.87	86.01	75.76	90.54	87.19	88.67	96.73	89.87
MXP	EX ANTE	69.91	78.56	72.09	83.88	80.19	86.88	96.47	89.88
Long	AMIDTS	71.64	75.76	74.59	80.29	76.28	95.95	94.31	95.29
	EX POST	68.89	78.09	70.28	80.97	84.21	86.19	86.71	91.97

Source: Prepared by authors with data from Bloomberg and Banco de México. Applying the E-Views 9 package

GARCH alternative; in fact, hedging effectiveness improves a lot at the 97.75% confidence level and at the 99.0% confidence level the best results are obtained.

Interestingly, for the short position in the MexDer, the more rigorous estimation is at a 95% level of confidence; but for the long position the best hedging strategy can be attained at a 99% level of confidence. In the case of the CME, for the short position the best metrics are at the 99%, but for the long position the best metrics are shared among the 95%, 97.5% and 99% levels of confidence.

The greatest protection for the short position during the turbulence period is attained with ESG at 95% confidence level; 95.48 represents the percentage reduction of the expected shortfall in the covered position compared to the uncovered position; when the coefficient approaches one (100% in our analyses to ease the interpretation of the results), there is a total decrease in risk; on the contrary, if it tends to zero, it implies that there is no reduction of risk in the MexDer; this can be attributed to futures volatility in the CME in normal market situations, while in tense situations the MexDer futures seemingly have lower volatility.

Finally, looking at the differences in performance between metrics, the best sample performance metric in the MexDer (and the entire sample) is that of the 95% ESG confidence level resulting in a 97.78, while the worst coverage performance corresponds to the VaRG with 68.49 (both in the short position); this represents a performance differential of 31 percent. In the case of the CME, the best hedging is obtained during the ex post period (96.73) for the short position (ES at 97.5%), whereas the worst coverage is achieved during the same subperiod 68.89 per cent (VaRG at 90%).

Summing up, exchange rate hedging in the Chicago Mercantile Exchange is more efficient applying ESG. The empirical evidence depends on the alphas (α) under consideration and the market to determine which of the two coverages should be used. Chicago is more convenient than hedging exchange rate in the Mexican Market. However, to ensure solid predictions ES-GARCH should be estimated at a 99.00% confidence level. Differences in the hedging strategies between the two markets are noteworthy. These differences can partially be attributed to market depth, traded volume, contract size, and market performance.[9] It is important to recall that the

[9] See also analysis of basic statistics, Table 3, page 12.

Table 6				
CME and MexDer Liquidity and Open Interest				
Chicago Mercantile Exchange Peso/Dollar Futures				
Period	**Volume**	**Notional Value**	**Open Interest**	**Exchange Rate**
Ex ante Oct-Dec 2016	7,100,313	172,175,518,270	278,790 (667,896)	0.0485
Amidts Jan-Mar 2017	310,000	8,246,654,784	298,003 (779,388)	00.54.96
Ex post April-June 2017	1,759,000	48,691,771,949	328,640 (831,460)	0.05536
Sum	**9,169,313**	**229,113,945,003**	**905,433 [2,278,744]**	
MexDer Dollar/Peso Futures				
Period	**Volume**	**Notional Value**	**Open Interest**	**Exchange Rate**
Ex ante Oct-Dec 2016	2,600,554	25,538,937,760	2,896,296	20.6194
Amidts Jan-Mar 2017	2,498,514	26,997,745,531	2,560,339	18.7955
Ex post April-June 2017	2,787,224	29,029,681,662	2,874,961	18.0626
Sum	**7,886,292**	**81,566,364,953**	**8,331,596**	
CME/MexDer	**1.63X**	**2.81X**	**0.1087 [27.35]**	

Source: Prepared by authors from Bloomberg and Baxmex data.

CME offered 46 currency futures in 2017 (now 48), while in Mexico currency futures are offered only for the peso/dollar and the peso/euro.

Complementing Table 1, Table 6 shows important asymmetries between the MexDer and the CME futures. As far as volume is concerned, overall, the CME is larger than the MexDer (1.63 times). Similarly, regarding notional value the CME is even larger; 2.81 times the size of the Mexican Market. However, in a very positive note, open interest is much higher in Mexico. A hypothetical number of open interest contracts in Chicago, assuming an equal size of contracts ($10,000 in both countries) was considered and adjusted by the end of each subperiod exchange rate. Even so, the Mexican market remains larger than the CME in open interest.

At any rate, the differences could be larger. While volume remains rather stable in the Mexican market, in the Chicago market there was a big drop after the first subperiod, particularly from the first to the second subperiod, the period of higher volatility. This can probably be attributed to investors' attitudes and institutional factors. As previously mentioned, the CME is a long large and well established market while the MexDer is a market still in the process of consolidation and growth. Feeling the upcoming of a period of turbulences derived from unfavorable economic conditions in Mexico, experienced hedgers in Chicago probably adjusted their holdings of dollar/peso futures migrating to other currencies. Finally, migration probably took place to the dollar/peso options market created by the CME in 2017. The differences also show the presence of segmentation among these markets and the possible existence of arbitrage opportunities.

5.3 Backtesting

This test was carried out for each partition from the sample series. The shaded areas in Tables 7 and 8 refers to the number of observations that are in the non-rejection area according to the statistical contrast made.

The number of failures of the estimates are well below the expected number of failures according to the parameters set out by the Kupiec test,

Table 7

"Backtesting VarG 95%
No rejection región for the number of observations (N) outside VaRG"

		Number of failures	Zone
Dollar Futures			
Dollar US	Ex Ante	2	
Short	Amidts	1	
	Ex Post	2	
Dollar US	Ex Ante	3	
Long	Amidts	3	
	Ex Post	2	
Peso Futures			
MXP	Ex Ante	4	
Short	Amidts	3	
	Ex Post	2	
MXP	Ex Ante	3	
Long	Amidts	3	
	Ex Post	2	

Source: Prepared by authors from calculations made in excel with sample data

Table 8			
"Backtesting Expected Shortfall (ESG) 95% No rejection región for the number of observations (N) outside VaRG"			
	Number of failures		Zone
Dollar Futures			
Dollar US	Ex Ante	4	
Short	Amidts	6	
	Ex Post	7	
Dollar US	Ex Ante	5	
Long	Amidts	3	
	Ex Post	7	
Peso Futures			
MXP	Ex Ante	4	
Short	Amidts	3	
	Ex Post	5	
MXP	Ex Ante	5	
Long	Amidts	7	
	Ex Post	7	

Source: Prepared by authors from calculations made in excel with sample data

Table 9				
Rejection region for the number of observations (N) outside the VaR				
"Significance level (Gray Zone)"		Days		
		T≤255	T≥510	T≥1000
0.001	1%	N < 7	1 < N < 11	4 < N < 17
0.05	5%	6 < N < 21	16 < N < 36	37 < N < 65
0.1	10%	16 < N < 28	38 < N < 65	81 < N < 120

Source: Prepared by authors from Kupiec information

Table 9. Therefore, our empirical evidence is statistically robust. The models applied are strong, and the most appropriate metrics to hedge against exchange risk can be chosen for either ex ante, during, and ex post volatility periods. The evidence is also a guide to select either the MexDer or else the CME for short and long positions. Results favor the application of the Expected Short Fall – GARCH model at very strict confidence levels of 99.0 percent.

Conclusions

This article contrasts the effectiveness of hedging exchange rate risk using two metrics most often applied in finance for the case of the peso/dollar traded in Mexico, and the dollar/peso traded in Chicago. The metrics used are VaRG and ESG applying a heteroscedasticity autoregressive GARCH (1,1) model.

The VaRG as a performance measure provides lower results in terms of better hedging performance than the results obtained with the ESG metric. This suggests that the magnitude of coverage performance effectiveness is related to the result that is intended to be achieved, since the results are based on the choice of a performance metric. ESG, as a metric for assessing coverage performance is statistically adequate; results obtained at a 99.0% confidence level are very rigorous. A caveat to its application must be added: the results are based on a specific period; ESG should be employed, like any other model, with caution and the support of continuing research.

Finally, this research underlines the importance of quantifying risk exposure; it is very important for all risk-return decisions concerning trade, investments corporate activity, and policy making, as well as for the choice of hedging alternatives. Further research is needed, particularly for the case of emerging markets and currencies subject to sharp volatility patterns. In the case of the U.S. and Mexican derivative markets further research is necessary to identify their differences and above all as a means to foster its integration with global markets as well as to the development and contribution to the advancement of the financial sector in Mexico and its potential to favor this nation's economic development.

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